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IZA DP No. 15182

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ISSN: 2365-9793

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ABSTRACT

People versus Machines: The Impact of Being in an Automatable Job on Australian Worker's Mental Health and Life Satisfaction

This study explores the effect on mental health and life satisfaction of working in an automatable job. We utilise an Australian panel dataset (HILDA), and estimate models that include individual fixed effects, to estimate the association between automatable work and proxies of wellbeing. Overall, we find evidence that automatable work has a small, detrimental impact on the mental health and life satisfaction of workers within some industries, particularly those with higher levels of job automation risk, such as manufacturing. Furthermore, we find no strong trends to suggest that any particular demographic group is disproportionately impacted across industries. These findings are robust to a variety of specifications. We also find evidence of adaptation to these effects after one-year tenure on the job, indicating a limited role for firm policy.

JEL Classification: I10, J20

Keywords: automation, life satisfaction, mental health, job security

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Introduction

Economists, policymakers and CEOs alike have projected that the world is on the cusp of the 'Fourth Industrial Revolution' (Schwab & Davis, 2018; Morgan, 2019). New and emerging technologies such as artificial intelligence, advanced robotics and the 'Internet of Things' are changing how people live, work and communicate with one another. While these innovations present opportunities for long run efficiency and productivity gains, they are also expected to create job displacement (Autor D. H., 2015) (Blien, Dauth, & Roth, 2021). It has been projected that over the next decade, new technologies will make 47% of jobs in the EU partially automatable, and 35% of jobs fully automatable (Josten & Lordan, 2019). Similar projections are made for the US, UK and other advanced economies (Frey & Osbourne, 2013; Josten & Lordan, 2019). Considering the projected scale of automation, understanding whether labour automation has detrimental effects on mental health and life satisfaction for workers has implications for public policy. However, little research has examined these potential impacts. The current study addresses this gap, by studying whether working in an automatable occupation is negatively associated with mental health and life satisfaction for Australian workers.

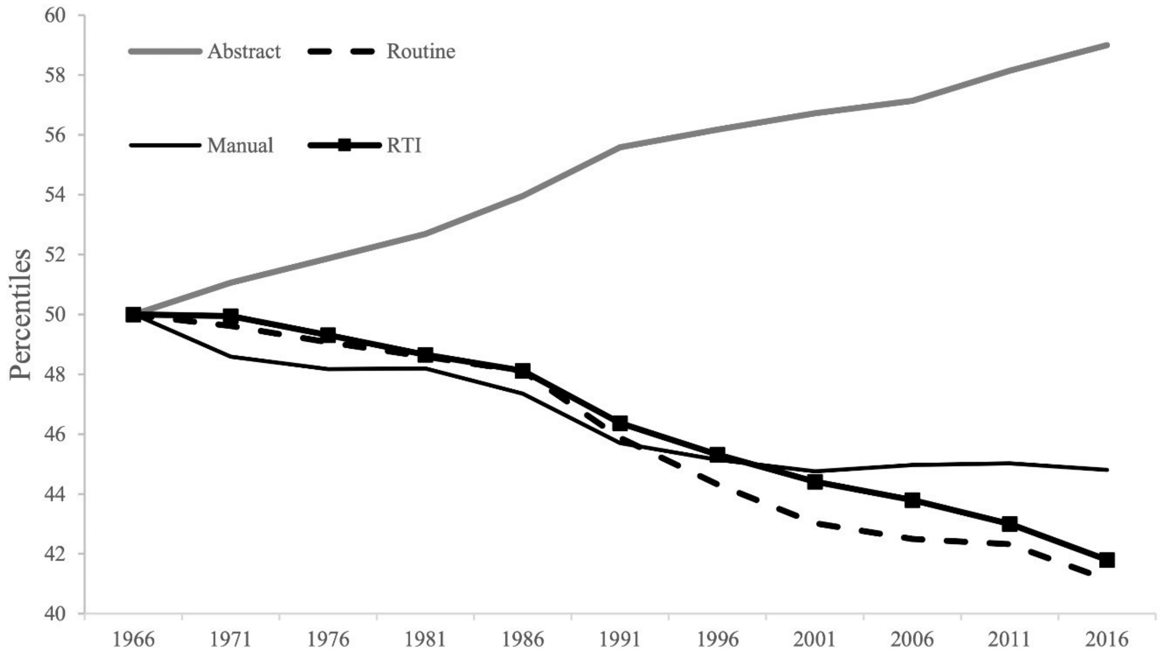
To understand how automation can change both the economy and society, researchers have focused on studying automation associated with the Third Industrial Revolution (characterised by the implementation of electronics and information technologies to automate processes, starting in the 1960s) (Xu, David, & Kim, 2018). The current study will take the same approach. It will look retrospectively to identify whether working in an 'automatable' job – one which is susceptible to substitution with technology – impacted the mental health and life satisfaction of Australian workers over the past two decades. We build on the work of Autor & Dorn (2013; 2015), which defines 'automatable' labour as being in a job which has a high proportion of routine tasks, which are most replicable by technologies such as computers and robots (Goos, Manning, & Salomons, 2014).

There is strong evidence to support this definition. Over the past several decades, there has been a substantive decline in demand for jobs with routine tasks across advanced economies (Autor & Dorn, 2013; Goos & Manning, 2007; Goos, Manning, & Salomons, 2014), including Australia. From *Figure 1*, the share of RTI across the Australian labour market declined markedly between 1955 and 2016 (Coelli & Borland, 2015).

Parallel to the expansion of labour automation literature, research on the use of mental health and life satisfaction as measures of social progress has been burgeoning (Frey & Stutzer, 2012; Lombardo, Jones, Wang, Shen, & Goldner, 2018; Diener, Oishi, & Tay, 2018). There is increasing recognition that these non-traditional metrics provide a valuable resource for monitoring social welfare and change (Dolan & Metcalfe, 2012; Stiglitz, Fitoussi, & Durand, 2018; Helliwell J. F., 2021). However, there has been little research to date which has explored the impact of automatable work on mental health and life satisfaction. Indeed, only two studies have looked at the association between job automation risk and mental health, providing initial correlational evidence that mental health is negatively related to automation, while none have looked at the effect of job automation risk on life satisfaction (Patel, Devaraj, Hicks, & Wornell, 2018; Abeliansky & Matthias, 2019).

This study contributes to the literature in the following ways. First, it is the first study to look at the association between job automation risk and life satisfaction. Second, we disaggregate the associations to identify heterogeneity by industry, age group, gender, and educational attainment. Finally, we explore whether there are aspects of mental health and life satisfaction which are associated with automatable work and could therefore influence mental health and life satisfaction.

Figure 1. Indices of the Demand for Labour to Perform Certain Tasks, Australia, 1966-2016



Notes. Each index is based at 50 in 1966. An increase indicates that changes in the occupational composition of the Australian workforce increased demand for that task characteristic, while a decline suggests the opposite. Graphic and data analysis produced by Coelli and Borland (2017). Original data sourced from the Australian Bureau of Statistics, 2017.

Source: Borland, J., & Coelli, M. (2017). Are Robots Taking our Jobs? The Australian Economic Review, 50(4), 377-397.

Background

Defining and Quantifying Automatable Work

Over the past several decades, the adoption of technologies such as computers, robotics and the internet have automated tasks that were previously completed by workers. Given these changes researchers have sought to identify what makes work automatable and which segments of the workforce are especially vulnerable. Over recent years, the prevailing theory has shifted from the so-called ‘skills-biased technological change’ hypothesis (SBTC) to the ‘routine-biased technological change’ (RBTC) hypothesis (Goos, Manning, & Salomons, 2014; Mondolo, 2020). Early empirical evidence initially supported the SBTC hypothesis, which theorises that technological innovations are disproportionately automating work which requires no, or limited, formal education and training (Katz & Murphy, 1992; Katz & Autor, 1999; Acemoglu, 2002; Katz & Goldin, 2009). Recent evidence has challenged this hypothesis.

Over the past two decades, research across the US, Europe, and other advanced economies has demonstrated a 'hollowing out' of middle-skill occupations, resulting in the 'polarisation' of skills across the workforce (Autor, Katz, & Kearney, 2006; Goos & Manning, 2007; Goos, Manning, & Salomons, 2014; Consoli & Sanchez Barrioluengo, 2019). This refers to declining demand for middle skill occupations, and simultaneous growth in demand for low and high-skilled occupations. The RBTC hypothesis provides a credible explanation for this 'job polarisation' phenomenon. The theory posits that instead of replacing low-skilled labour, new technologies are substituting jobs which are high in RTI (those which have a high concentration of routine cognitive and routine manual tasks) (Autor & Dorn, 2013). This is proposed on the basis that emerging technologies are most suited to tasks which are systematic and procedural, as these are most easily codified. As such, occupations high in RTI are more susceptible to substitution with technology (Acemoglu & Autor, 2011). To test this hypothesis, Autor and Dorn (2013; 2015) classified each occupation in the *US Dictionary of Occupation Titles* as 'automatable' according to their level of RTI. They find that jobs highest in RTI were disproportionately lost, while there were simultaneous gains made in jobs with higher levels of abstract tasks (those which involve creativity, problem solving and coordination). They argue that this polarisation is the result of automation of routine labour, and the consequent reallocation of labour supply to jobs which are complementary to new technologies (which are concentrated in high-skill occupations and low-skilled service occupations). Autor and Dorn's findings have been replicated across numerous economies, including Australia (Autor, Dorn, & Hanson, 2015;

Das & Hilgenstock, 2018; Gregory, Solomons, & Zierahn, 2019; Østergaard & Holm, 2018; Yuhong & Xiahai, 2020, Blien, Dauth, & Roth, 2021; Coelli & Borland, 2015).

Importantly, the literature indicates that automation of labour has occurred disproportionately across the workforce, particularly by industry, skill-level and demographic group. Evidence suggests that industries such as manufacturing, which held a greater concentration of routine tasks, have seen higher levels of labour automation than other industries, particularly among men (Autor, Dorn, & Hanson, 2015; Autor, Dorn & Hanson, 2019). Mirroring these findings, Lordan and Neumark (2018) and Lordan (2021) observe that following a minimum wage increase, the share of automatable labour declines most sharply for older workers in the manufacturing industry. The authors also find that workers in some demographic groups are more susceptible to negative outcomes, including female and black workers, and those in the oldest and youngest age groups. Similar trends are observed across the UK (Lordan, 2021). Other research suggests that younger workers, particularly men, are susceptible to job displacement, as they often perform manual tasks which are susceptible to automation (Dauth, 2014).

The Relationship between Automation, Life Satisfaction and Mental Health

For the majority of the last century, the wellbeing and progress of a society has been measured using traditional economic metrics, such as Gross Domestic Product. Recently however, social scientists have become interested in using more diverse measures of welfare, such as life satisfaction (Kahneman & Deaton, 1997; Stiglitz, Sen, & Fitoussi, 2009; OECD, 2013). As such, scientists studying life satisfaction *"do not prejudge what people will consider a good life for themselves, but instead rely on the judgements respondents themselves provide, based on whatever criteria research participants deem to be most important."* (Diener, Oishi, & Tay, 2018).

The rapidly expanding literature on life satisfaction has identified a range of factors which influences an individual's life satisfaction, including income, education, health and unemployment (Adler, Dolan, & Kavetsos, 2017; Das, et al., 2020). These studies typically rely on survey responses regarding self-reported life satisfaction (as we do here), positive or negative affect, or the sense of purpose or meaning in one's life (Dolan & Metcalfe, 2012). Such measures of life satisfaction have been found to be credible and psychometrically valid (Diener, Inglehart, & Tay, 2012; Helliwell, 2018).

Of the factors which have been found to predict life satisfaction, mental health has been shown to be the strongest (Layard, Chsholm, Vikram, & Shekhar, 2013). Importantly, although strongly correlated to life satisfaction, mental health is distinct. Keyes' complete mental health model (2007) specifies that wellbeing relates to positive psychological and social functioning, while mental illness refers to the presence of a range of mental disorders. This definition indicates that the absence of mental illness does not indicate wellbeing, and the absence of wellbeing does not imply the presence of mental illness.

Although the literature on both labour automation and the sources of life satisfaction and mental health have both been expanding over the past decade, we find no research which examines the relationship between job automation risk and life satisfaction. Adjacent literature does explore related concepts such as the effect of fear of robots on life satisfaction, and finds evidence of a negative association (McClure, 2017; Hinks, 2020; Schwabe & Castellacci, 2020; Stankeviciute, Staniškiene, & Ramanauskaite, 2021)). However, they rely on a subjective measure (fear) rather than using an objective measure of job automation risk, as we do here. There are two studies which have explored the relationship between job automation risk and mental health outcomes, both of which find a negative relationship. (Patel, Devaraj, Hicks, & Wornell, 2018) and Abeliansky and Beulmann (2019) for the US and Germany respectively. As such, there is opportunity for further research to explore whether more sizeable effects are found in occupations which are most easily codified.

Job Automation Risk Channels for Mental Health and Subjective Wellbeing

There has been little analysis to date on the mechanisms through which job automation risk affects mental health and life satisfaction. The studies which have been completed propose job precarity as the primary channel through which job automation risk may influence mental health (Patel, Devaraj, Hicks, & Wornell, 2018; Abeliansky & Matthias, 2019). Adjacent literature presents a strong theoretical basis for this hypothesis (Khubchandani & Price, 2017; Watson & Osberg, 2019). Indeed, a meta-analysis of 57 longitudinal studies concludes that there is "*clear evidence for the impact of job security on future mental/psychological well-being"* (De Witte, Pienaar, & De Cuyper, 2016). Further, research has found that the threat of job loss induces even greater psychological distress than the actual occurrence of job loss (Watson & Osberg, 2018). Therefore, considering that job automation risk increases job insecurity, it would seem to follow that working in an automatable job has a detrimental effect on mental health and life satisfaction by inducing job insecurity (Heaney, Israel, & House, 1994; Lordan & Neumark, 2018; Kronenberg & Boehnke, 2019).

Notably, the literature differentiates between 'quantitative' and 'qualitative' job security, where quantitative job insecurity refers to concerns about the future of the present job, while qualitative refers to broader concerns around lack of career opportunities, decreasing salary development and deterioration of working conditions. Arguably, working in an automatable occupation has the potential to negatively affect perceptions of both quantitative and qualitative job security, and thus negatively impact mental health and life satisfaction. Indeed, previous research has demonstrated several related factors which influence workers' perceptions of job security, including economic conditions, level of education, temporary employment and employment in manual labour (Munoz de Bustillo & de Pedraza, 2010; Lübke & Erlinghagen, 2014; Kuroki, 2012; Naswall & De Witte, 2003).

In accordance with Autor and Dorn's (2013) definition, automatable work is that which is high in RTI. Yet routine and repetitive work has itself been linked with negative impacts on mental health and life satisfaction due to the induction of boredom (O'Hanlon, 1980; Seckin, 2018). Indeed *"task characteristics have been seen as the main cause of workplace boredom… (particularly) characteristics such as repetitiveness and monotony"* (Tsai, 2016; Loukidou, Loan-Clarke, & Daniels, 2009). In turn, workplace boredom is associated with both higher instances of depression and reduced life satisfaction (Johansson, Aronsson, & Lindstrom, 1978; Weisner, Windle, & Freeman, 2005; Smith, 1981). As such, it is conceivable that detrimental effects on mental health and life satisfaction of persons in automatable occupations may be more symptomatic of working in highly routine jobs than exposure to job insecurity, implying that job destruction may have positive impacts on wellbeing in the future, assuming that the jobs destroyed are replaced.

There is additional research which also suggests that automation may augment wellbeing. Indeed, recent research has shown that penetration of industrial robots is negatively associated with the physical health of low-skilled populations (Gunadi & Ryu, 2021). Similarly, it is important to consider that some of the characteristics of automatable occupations may have a *positive* association with mental health and life satisfaction. For example, research suggests that occupations which induce high levels of job satisfaction, better work-life balance and lower levels of stress are associated with higher levels of mental health and life satisfaction (Aydintan & Koc, 2016; Haar, Russo, Sune, & Ollier-Malaterre, 2014; Erdogan, Bauer, Truxillo, & Mansfield, 2012). As such, if these characteristics are associated with automatable occupations, it is conceivable that working in an automatable occupation could be associated with *higher* levels of mental health and/or life satisfaction.

Testable Hypotheses

The current study aims to explore (1) the possible mental health and wellbeing risks of exposure to job automation risk; (2) whether workers across different industries and demographic groups are disproportionately impacted by job automation; and (3) whether there are particular aspects of health and life satisfaction which are associated with working in an automatable occupation. Accordingly, the study tests the following hypotheses:

H1A. Job automation risk is negatively associated with mental health.

H1B. Job automation risk is negatively associated with life satisfaction.

H2A. Job automation risk has a greater detrimental impact on the mental health of persons in demographic groups which are more susceptible to job displacement.

H2B. Job automation risk has a greater detrimental impact on the life satisfaction of persons in demographic groups which are more susceptible to job displacement.

H3A. Job automation risk has a negative association with physical and general health, which could therefore influence mental health.

H3B. Job automation risk has a negative association with employment opportunities, which could therefore influence life satisfaction.

Methodology

Data

We draw on the HILDA household-based longitudinal survey. This is a panel dataset collected since 2001 on a broad range of economic, social and demographic indicators (Watson & Wooden, 2012). The current study utilises the 18th release of the HILDA dataset, which contains 18 waves of data (from 2001 to 2018), collected annually using face-to-face interviews and self-completion questionnaires. While all household members are enumerated in the data collection process, individual and household level data are collected only for those who are 15 and older, and therefore, the current research is restricted to this age range. In the first wave of the survey, the sample consisted of 19,914 people (7,682 households). An additional 5,462 persons (2,153 households) were added to replenish the sample in Wave 11 (2011). Of the respondents who completed interviews in Wave 1, 62% remained in the sample by Wave 18, while 75.9% of the 'top up' sample remained in the study.

The current study constructed a strongly balanced panel from the available 18 waves of data, which are representative of the Australian population (Watson & Wooden, 2012), though a robustness check in which the same analysis was undertaken on the unbalanced panel was also undertaken. Individuals for whom the observations for the outcome variables were missing, incomplete or invalid were excluded. As the independent variable used in this study is a binary classification of job automation risk, the sample was also restricted to persons whose labour force status was *'Employed'* across all waves, rather than *'Unemployed'* or *'Not in the Labour Force'*. This decision was made to investigate the impact of working in an automatable job on mental health and life satisfaction, separate to the impact of employment status change. Finally, the sample was restricted to those industries which mapped to Autor and Dorn's automatability classifications, resulting in three industry classifications being omitted from the sample (Agriculture, Forestry & Fishing and Mining, Electricity, Gas and Water Waste & Other Services). Following the application of these restrictions, the aggregated sample analysed included 41,923 observations. A table summarising the exclusion steps and resulting number of observations is included in *Appendix 3*.

Occupational Automatability

This study looks at the impact of job automation risk on mental health and life satisfaction outcomes. We create a binary independent variable which classifies an occupation as 'automatable' or 'non-automatable'. To do so, we developed a crosswalk (displayed in *Appendix* 2) between the 2-Digit 2006 *Australia New Zealand Standard Classification of Occupations* (ANZSCO) and Autor et. al.'s (2013; 2015) job automation classification (Australian Bureau of Statistics, 2006). This classification has been developed using routine task intensity (RTI) as a proxy for the degree to which an occupation is automatable. The authors define an occupation as automatable where it has been found to be the top third of the employment-weighted distribution of RTI across occupations. RTI is expressed by the following equation:

$$RTI_k = ln\ (T_k^R) - ln\ (T_k^M) - ln\ (T_k^A) \qquad (1)$$

Where T_k^R, T_k^M, and T_k^A are the levels of routine, manual and abstract task intensity, respectively, for each occupation, k. The extent to which an occupation is concentrated in each of these levels of task intensity has a direct effect on the extent to which it is classified as susceptible to automation. Higher levels of RTI are associated with higher susceptibility to automation, as this signifies a high concentration of tasks which are repetitive and thus codifiable. Manual tasks are often more sporadic in sequence, and thus are less susceptible to automation. Finally, abstract tasks require creativity, problem-solving and high-level thinking, which are substantially less susceptible to substitution than both routine and manual tasks, and indeed, are complementary to integration of technology. Of the 41,923 observations used in the aggregate sample, 10,420 are classified as ‘automatable’ occupations, and the remaining 31,503 observations are classified as ‘non-automatable’.

Mental Health

This study utilises the Mental Health Inventory (MHI-5) of the Short Form instrument (SF-36), which has been validated as a reliable measure of mental health (Butterworth & Crosier, 2004; Sanson-Fisher & Perkins, 1998). The scale is constructed using five question items which ask participants to list the number of times in the previous four weeks in which they have: *a)* been nervous, *b)* felt so down in the dumps that nothing could cheer them up, *c)* felt calm and peaceful, *d)* felt down and *e)* been happy. Responses are incorporated into a single score on a 0-100 scale, with a higher score is indicative of better mental health. To enable ease of interpretation between outcome variables, the variable was standardised to have a mean of zero and a standard deviation of one.

Life Satisfaction

The second outcome variable is life satisfaction, which is derived from the HILDA survey question: *“All things considered, how satisfied are you with your life?”* (Summerfield, et al., 2019). The response is provided on an 11-point scale, from 0-10, with a higher numerical value representing higher levels of life satisfaction, based on the Comprehensive Quality of Life Scale (ComQol) (Cummins, 1996). This variable was also standardised to have a mean of zero and a standard deviation of one.

1.1 Descriptive Statistics

Table 1 displays the descriptive statistics for the two outcome variables (mental health and life satisfaction) by both the aggregated sample, as well as by automatability classification (a more detailed breakdown can be found in Appendix 4a and Appendix 4b). This data highlights that working in an automatable occupation is associated with a 0.14 standard deviation reduction in mental health outcomes. A t-test confirms there is a statistically significant difference (p=0.039). Similarly, those working in automatable occupations report life satisfaction outcomes which were 0.14 standard deviations below the mean, and this relationship is statistically significant (p=0.050).

Table 1. Descriptive Statistics for Key Outcome Variables, by Aggregate Sample and Automatability Classification

	Aggregated Sample	Automatable Occupations	Non-Automatable Occupations		
	Means (SD)	Means (SD)	Means (SD)	Mean Difference	*p-value*
Mental Health (SF-36) (SD)	0.000 (1.000)	-0.005 (1.010)	0.002 (0.997)	0.007 (0.011)	0.557
Life Satisfaction (SD)	0.000 (1.000)	-0.014 (1.019)	0.00 (0.993)	0.021 (0.011)	0.056
N	41,923	10,420	31,503	-	-

Notes. Data from HILDA 18th Release. Means displayed (proportions in the case of binary variables). Standard deviations in parentheses. 'Automatable and 'Non-automatable' groups created by assigning each of the 2-digit ANZSCO occupation codes available in the HILDA dataset to the binary classification, using a crosswalk (Appendix 1) with Autor & Dorn's (2013) occupation classification.

To investigate the impact of working in an automatable occupation on mental health and life satisfaction we estimate:

$$\gamma_{jiat} = b_1 \cdot Automatable_{jiat} + I_j + T_t\gamma + A_a\,\lambda + \varepsilon_{jiat} \qquad (2)$$

Where γ_{jiat} is the outcome variable of interest (mental health or life satisfaction) of the jth person in industry in area a, at time t. $Automatable_{jiat}$ is a binary variable which assumes a value of one if a person is employed in an occupation classified as 'automatable' at a time *t*, and a value of zero if they are employed in a non-automatable occupation. Ij refers to the individual-level fixed effects for an individual j. The equation also includes area (A_a) and time (T_t) fixed effects, and standard errors are two-way clustered by occupation and industry.

We estimate (2) on our full sample, and then separately by industry, age, gender and level of education. For industry we consider differences by one digit industry code: construction, manufacturing, transport, wholesale, retail, finance, services and public administration. When disaggregating by industry, we include only persons who moved within the same industry classifications rather than between industries. This ensures that we accurately capture associations between moving between automatability classifications and not moving between industries. Therefore, we disaggregate the sample population by gender and age (those between the ages of 15 and 39 and those over the age of 40). We consider separate analysis by three distinct levels of educational attainment: *'No non-school qualifications'*, *'Tertiary certificate of diploma'* and *'Bachelor's degree or Postgraduate Study'*. We also run a robustness analysis which disaggregates by levels of income and labour union status (*Appendix 5.10*).

Equation (2) captures associations between those who transition between automatability classifications. Therefore, we also conduct further analyses to identify whether moving into an automatable occupation is associated with detrimental association with mental health and life satisfaction. Specifically, we disaggregate the results into two groups: those who move into automatable occupations (non-automatable job→ automatable job), and those who move into non-automatable occupations (automatable job → non-automatable job). This enables identification of whether the differences in reported mental health and life satisfaction are associated with working in an automatable, or non-automatable job specifically. Indeed, if moving *into* an automatable occupation is associated with a reduction in mental health or life satisfaction, it can be inferred that working in an automatable occupation is associated with lower mental health. Similarly, if moving out of an automatable occupation is associated with an improvement in mental health, the same conclusion will be reached.

We attempt to identify channels through which automatable work influences mental health and life satisfaction. We utilise *Equation (2)* to look at the effect of automatable work on specific aspects of health and life satisfaction. These include the domains of health, including physical health, general health, emotional role, physical role, bodily pain, social function and vitality. The measures of life satisfaction include satisfaction with one's home, employment opportunities, financial situation, safety, local community, health, neighbourhood, and amount of free time. If any one of these is associated with working in an automatable occupation, it would indicate that this factor may be a channel through which mental health and life satisfaction are influenced by job automation exposure.

Identification Strategy

Considering that workers were not randomly assigned to the occupation in which they work, there are likely to be systemic differences between these groups. *Equation (2)* was selected as the most appropriate model as it reduces the risk of omitted variable bias by controlling for 'fixed' factors, both observed and unobserved. This includes individual level fixed effects which are time-invariant, such as genetics, and other individual characteristics which remain constant across time, and time-fixed effects, which change consistently across the population over time, such as changing economic conditions and national policy changes. The inclusion of area-fixed effects controls for consistent differences across regions, such as employment opportunities, local or state-level public policies and environmental factors. Controlling for these 'fixed effects' is particularly important in the context of the current research, as many factors external to occupational automatability influence mental health and life satisfaction. As a robustness check, we also conduct the analysis excluding individual level fixed effects *(Appendix 5.8).*

While the fixed effects model controls for both observed and unobserved variables, the risk of endogeneity is not fully eliminated. We therefore run several robustness checks. These include three models which include a range of additional controls, including income, marital status, race, socio-economic disadvantage and age (*Appendix 5.1*); and age and age squared (*Appendix 5.2*); hours worked, income per hour worked and tenure in role (*Appendix 5.3*). An additional robustness check includes area-by-time fixed effects to control for area-specific economic shocks in any given year (*Appendix 5.4*). We also include a robustness check which lags the outcome variables by one year to identify whether there are legacy effects of moving between automatability classifications (*Appendix 5.5*, in addition to an analysis on the unbalanced panel (*Appendix 5.6*). Additionally, we conduct a robustness check using a continuous automatability variable (*Appendix 5.7)*.

Results

Table 2 presents results of the fixed effects regression model expressed by *Equation (2)*, both by full sample and by industry. Notably, we do not find statistically significant associations on either mental health or life satisfaction across the pooled sample. We do, however, find evidence of small statistically significant associations (between 0.082 and 0.150 standard deviations) within particular industries. As a reference for the size of mental health effects of other life events, unemployment has been shown to reduce mental health of unemployed persons by 0.51 standard deviations compared to those who remain employed (Paul & Moser, 2009). Interestingly, the signs of the associations found are not always in the expected direction. This suggests that for some industries automatable work may actually augment mental health and life satisfaction, and goes against the idea that the worst jobs are being automated (Katz & Autor, 1999) (Katz & Goldin, 2009).

Differing associations across industries can intuitively arise given the tasks within occupations in each industry differ. As shown in *Table 2*, we find small positive significant mental health associations for those in the construction, transport, retail and manufacturing (albeit manufacturing is significant at the 10% significant level). These are the same industries which previous research has identified as most susceptible to job displacement for workers in automatable work (Lordan & Neumark, 2018) and Lordan (2021). This implies that for these industries the work that is being replaced is wellbeing promoting. For construction, transport, retail and manufacturing moving between automatability classifications is associated with a 0.162, 0.150, 0.167 and 0.082 standard deviation improvement in mental health, respectively. Conversely, we find negative associations, significant at the 10% level for persons working in the wholesale industry.

These findings are robust across the additional controls models (*Appendices 5.1, 5.2, 5.3, 5.4*), though not across the lagged model (*Appendix 5.6*). This indicates that people may adapt, which is consistent with literature showing that people's mental health reverts back to a baseline measure following most major life events (Odermatt & Stutzer, 2019). It also implies a limited role for firm policy.

Returning to Table 2 there are negative associations on life satisfaction of being in automatable work and working in retail and public administration. These estimates can be viewed as moderate or small associations, as compared with events such as unemployment, which previous literature has shown to have a 0.6 standard deviation reduction in life satisfaction with low levels of adaptation (Clark & Oswald, 1994). These conclusions are also robust to the inclusion of additional controls (*Appendices 5.1, 5.2, 5.3*), area-by-time fixed effects (*Appendix 5.4*), continuous automation variable *(Appendix 5.7),* considering the unbalanced panel (with the exception of construction, and we note the coefficients are though attenuated using this sample (*Appendix 5.6*) the exclusion of fixed effects (*Appendix 5.8*). We note that in a lagged model, the estimates unanimously centre closer to zero and are not significant, perhaps suggesting adaptation to current work circumstances for those that stay in the same employment type but do not remain after a year (*Appendix 5.5).*

Heterogeneous Effects by Age and Gender

To identify heterogeneous associations, *Tables 3* and 4 present the results broken down by age, gender and highest level of educational attainment. When disaggregating by age group, we find strongly significant and positive associations observed across the aggregate population among workers over the age of 40. These results appear to be driven by workers within the construction, transport and retail industries, which all demonstrate positive and statistically significant associations. Correspondingly, the negative and weakly significant associations within the wholesale industry are driven by strongly significant and sizeable negative associations among younger workers (15-39 years old). Indeed, the negative mental health associations for this group are comparable with the size of the effect of unemployment, as demonstrated in previous research (Paul & Moser, 2009).

Disaggregating the results by gender highlights further heterogeneity. As shown in *column (2),* the positive associations are substantially larger for women than men in the construction and manufacturing industries. Similarly, the positive associations in the retail industry are driven by larger and more significant associations among women, while the associations on the transport industry are only statistically significant for men.

In contrast with these results, the associations among both women and university-educated persons in the services sector are *negativ*e, both of which are significant at the 1% level. Conversely, we find strongly significant, positive associations for those with a university-level education in the construction sector. We also find positive and significant impacts on mental health for mid-skilled workers in the construction sector, and low-skilled workers in the transport sector.

Similar patterns are observed among middle-income and unionised workers (*Appendix 5.10).* Overall, these findings suggest that the associations across the full sample, shown in *Table 2,* mask significant heterogeneity by demographic group. Indeed, the positive effects are driven by persons over the age of 40. While the patterns by gender and highest level of educational attainment are less consistent, effects are larger and more significant among women. While the magnitude of effects are mostly small, there are some subgroups which see moderate impacts on mental health, particularly those in the construction and manufacturing industries, such as women and university-educated workers. These associations are robust across a model specification with additional controls (*Appendices 5.1, 5.2, 5.3, 5.4)*.

Moving to the disaggregated results on life satisfaction displayed in *Table 4*, we find further evidence of heterogeneous associations across demographic groups. Indeed, disaggregating associations by age highlights that detrimental associations on life satisfaction in the finance industry are driven by those over the age of 40, while detrimental associations in the retail industry are larger, and only statistically significant among those aged 15-39 years. Younger workers also drove associations within the wholesale industry, although this effect was positive. Disaggregating results by gender highlights that negative associations on

Table 2. Effect of Working in an Automatable Occupation on Mental Health and Life Satisfaction

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable Occupation	0.015	0.162***	0.082**	0.150***	-0.098*	0.167***	-0.015	-0.040	-0.007
	(0.014)	(0.059)	(0.036)	(0.058)	(0.058)	(0.062)	(0.054)	(0.027)	(0.033)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	0.004	-0.044	0.049	0.026	0.068	-0.108*	-0.060	-0.032	-0.065**
	(0.0142)	(0.0795)	(0.0369)	(0.0568)	(0.0628)	(0.0598)	(0.0468)	(0.0278)	(0.0318)
N	41,900	2,834	5,836	2,115	1,101	3,306	2,281	15,147	11,059

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

OLS regression estimates were also calculated and are displayed in *Appendix* 5.9

Table 3. Disaggregated Effects of Working in an Automatable Occupation on Mental Health (SF-36)

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Age Group									
15-39 Years old									
Automatable	-0.047*	0.103	-0.046	0.020	-0.406**	0.020	-0.015	-0.075	-0.035
Occupation	(0.027)	(0.066)	(0.061)	(0.112)	(0.171)	(0.098)	(0.103)	(0.064)	(0.072)
N	11,499	887	1,275	403	242	1,339	699	4,247	2,407
Over 40 years old									
Automatable	0.040**	0.196**	0.074*	0.143**	-0.068	0.191**	-0.016	0.002	-0.007
Occupation	(0.0158)	(0.080)	(0.043)	(0.068)	(0.066)	(0.082)	(0.065)	(0.028)	(0.037)
N	30,401	1,947	2,782	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	0.015	0.136**	0.033	0.138**	-0.123*	0.086	0.046	0.064	-0.061
Occupation	(0.019)	(0.060)	(0.039)	(0.064)	(0.072)	(0.110)	(0.068)	(0.041)	(0.051)
N	19,963	2,514	3,120	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.011	0.409*	0.275***	0.177	-0.046	0.190***	-0.044	-0.080**	0.021
Occupation	(0.020)	(0.214)	(0.087)	(0.134)	(0.103)	(0.073)	(0.076)	(0.034)	(0.043)
N	21,937	320	937	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
No non-school qualifications									
Automatable	0.002	0.092	0.061	0.209***	-0.141*	0.123	-0.079	0.005	0.013
Occupation	(0.021)	(0.077)	(0.051)	(0.076)	(0.081)	(0.081)	(0.068)	(0.044)	(0.060)
N	13,538	947	1,647	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.075*	0.245**	0.079	0.053	0.056	0.071	0.142	0.082*	-0.006
Occupation	(0.025)	(0.104)	(0.057)	(0.100)	(0.129)	(0.123)	(0.125)	(0.045)	(0.061)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.014	0.451***	0.258*	-0.257	-0.135	0.230*	-0.061	-0.138***	-0.004
Occupation	(0.027)	(0.146)	(0.131)	(0.268)	(0.117)	(0.127)	(0.096)	(0.045)	(0.052)
N	14,199	270	904	157	252	402	837	6,044	5,641

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. The model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Subgroups were constructed by restricting the analysis to those in different demographic groups. Age groups are into those between the ages of 15 and 39 and those over the age of 40. Gender is restricted to male and female. Education is restricted to 3 groups: 'No non-school qualifications', 'Tertiary certificate of diploma' and 'Bachelor's degree or Postgraduate Study'.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Disaggregated Effects of Working in an Automatable Occupation on Life Satisfaction

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Age Group									
15-39 Years Old									
Automatable	-0.016	-0.107	-0.070	-0.182	0.297**	-0.306***	0.051	0.036	-0.067
Occupation	(0.029)	(0.214)	(0.068)	(0.113)	(0.135)	(0.088)	(0.079)	(0.048)	(0.066)
N	11,499	887	1,999	403	242	1,339	699	4,247	2,407
Over 40 Years Old									
Automatable	-0.001	-0.042	0.022	0.008	0.037	-0.028	-0.131**	-0.031	-0.052
Occupation	(0.017)	(0.063)	(0.044)	(0.060)	(0.071)	(0.069)	(0.061)	(0.034)	(0.036)
N	30,401	1,947	3,837	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	-0.002	-0.072	0.042	0.012	0.017	-0.096	-0.006	-0.014	-0.081
Occupation	(0.021)	(0.086)	(0.042)	(0.058)	(0.079)	(0.103)	(0.062)	(0.048)	(0.050)
N	19,963	2,514	4,324	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.010	0.229*	0.081	0.125	0.156	-0.169**	-0.0904	-0.040	-0.056
Occupation	(0.020)	(0.136)	(0.077)	(0.159)	(0.114)	(0.073)	(0.066)	(0.0337)	(0.041)
N	21,937	320	1,512	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
No non-school qualification									
Automatable	-0.048**	-0.211	-0.034	0.028	0.002	-0.183**	0.0146	-0.024	-0.086
Occupation	(0.023)	(0.131)	(0.058)	(0.068)	(0.083)	(0.079)	(0.068)	(0.047)	(0.065)
N	13,538	947	2,418	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.081***	-0.0223	0.151***	-0.0416	0.359**	-0.140	-0.111	0.0318	-0.0376
Occupation	(0.026)	(0.0941)	(0.0497)	(0.115)	(0.144)	(0.0958)	(0.0960)	(0.0477)	(0.0616)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
Bachelor or Above									
Automatable	-0.009	0.291**	-0.085	0.344**	-0.096	-0.057	-0.082	-0.089*	-0.059*
Occupation	(0.016)	(0.103)	(0.106)	(0.157)	(0.089)	(0.124)	(0.052)	(0.045)	(0.033)
N	18,724	270	904	157	252	402	837	6,044	5,641

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10. Subgroups were constructed by restricting the analysis to those in different demographic groups. Age groups are into those between the ages of 15 and 39 and those over the age of 40. Gender is restricted to male and female. Education is restricted to 3 groups: 'No non-school qualifications', 'Tertiary certificate of diploma' and *'Bachelor's degree or Postgraduate Study'.*

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**** p<0.01, ** p<0.05, * p<0.1*

life satisfaction in the retail industry are more sizeable and statistically significant for women than for men. Examining associations by education level show that moving between automatability classifications has a positive association with life satisfaction for middle-skill workers across the aggregate population sample, seemingly driven by the effects among those in the manufacturing and wholesale industries (significant at the 1% level), but lower life satisfaction for lower-skilled workers across the aggregate population, predominantly within the retail industry. This suggests that the ‘job polarisation ‘hypothesis may extend to mental health across these industries.

Effects by Direction of Job Automatability Classification Movement

Tables 5 and *6* present the results of the fixed effects model, disaggregated by direction of movement between automatability classification. This is intended to identify whether observed associations on mental health and life satisfaction are driven by movement into, or out of, automatable occupations, we find that while there are no significant associations across the aggregated sample, the positive associations observed on mental health are predominantly driven by movement *out* of automatable occupations (into-non-automatable occupations). Indeed, across the construction, manufacturing, transport and retail industries, moving out of an automatable job improves mental health. For the transport industry, a move *into* an automatable occupation also improves mental health. This may suggest that for these industries, moving jobs in general has a positive effect on mental health, but these associations are more pronounced for people moving *out* of automatable work. These results may also suggest that the observed associations of moving into automatable occupations are downward biased, and the associations of moving into a non-automatable occupation are upward biased due to the positive wellbeing associations of moving to a new job in general (Di Tella, Haisken De-New, & MacCulloch, 2010). Overall, these patterns suggest that moving out of an automatable occupation improves mental health, particularly in industries which have seen high levels of routine-work displacement (Lordan & Neumark, 2018).

Significantly, there is a major exception to the pattern: moving to a non-automatable occupation has a negative effect on mental health for persons in the services industry. This finding tracks with evidence that services occupations are the only low-skilled jobs which have seen growth over the past few decades, due to the high concentration of non-automatable, low-skill occupations unique to this industry (Autor & Dorn, 2013). Therefore, it is conceivable that a move to a non-automatable job does not improve the mental health of workers in the services industry as these workers were not experiencing job insecurity. As such, overall the findings suggest that moving out of automatable work improves mental health for industries in which automatable work has become more precarious.

Table 6 displays the results on life satisfaction, disaggregated by direction of movement into or out of automatable work. These results highlight a similar pattern to those observed on mental health: moving out of automatable work improves life satisfaction for those in manufacturing, with the notable exception of the services sector, suggesting that job automation risk could have a detrimental effect on life satisfaction. This is further evidenced by the fact that workers who move *into* automatable occupations experience negative associations on their life satisfaction. Workers in both the retail and public administration industry saw a statistically significant decline in life satisfaction of 0.140 and 0.093 standard deviations, respectively. These observations provide further evidence that working in an automatable occupation has a detrimental impact on life satisfaction.

Table 5. Effect of Working in an Automatable Occupation on Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupations)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Move to automatable job									
Automatable Occupation	0.020	0.075	0.0759*	0.172**	-0.074	0.134*	0.023	-0.029	0.012
	(0.0156)	(0.0488)	(0.0449)	(0.0820)	(0.0674)	(0.0689)	(0.0714)	(0.0328)	(0.0382)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.012	0.280**	0.134***	0.180**	-0.105	0.304***	-0.080	-0.113***	0.010
	(0.0164)	(0.112)	(0.0481)	(0.0761)	(0.0791)	(0.0819)	(0.0652)	(0.0344)	(0.0409)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. The model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Subgroups were constructed by restricting the sample to those who moved into automatable work (Row 1) and those who moved into non-automatable work (Row 2).
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Effects by Domains of Mental Health and Life Satisfaction

The evidence thus far has looked specifically at associations on the two outcome variables of interest: mental health and life satisfaction. To identify whether these associations are driven by particular aspects of health and life satisfaction, such as employment opportunities, *Tables 7* and *8* show the regressions on domains of mental health and life satisfaction. As shown in *Table 7*, working in an automatable occupation has a statistically significant association with only one of the aspects of the SF-36 health domains: physical health. The negative associations with bodily pain are also significant at the 10% level. This relationship is unsurprising considering the high concentration of manual tasks in 'automatable' occupations, and is in agreement with previous literature which has shown that increased automation is associated with improved physical health among lower-skilled workers (Gunadi & Ryu, 2021). As physical health is a strong determinant of mental health, these associations may explain some of the observed heterogeneity by industry, such as stronger associations in the construction industry, which has a high concentration of routine manual labour (Dolan, Peasgood, & White, 2008) (Autor & Dorn, 2013).

Table 8 presents the regressions on each of the nine aspects of life satisfaction collected by the HILDA survey. This analysis highlights that there is a strongly significant negative effect found on worker satisfaction with employment opportunities. Although this effect is small, it supports the theory that job insecurity is a mechanism through which job automation risk influences life satisfaction. Furthermore, we also find positive associations on free time, which are small but significant at the 1% level. These findings reflect previous literature which has identified that life satisfaction is closely tied with how we spend our time, and particularly the balance between factors such as hours spent working, commuting and exercising (Dolan, Peasgood, & White, 2008; Luttmer, 2005; Biddle & Ekkekakis, 2005).

Table 6. Fixed Effects: Effect of Working in an Automatable Occupation on Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupations)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Move to automatable job									
Automatable Occupation	-0.003	-0.101	0.059	-0.008	0.016	-0.140**	-0.043	-0.028	-0.093***
	(0.0159)	(0.0951)	(0.0477)	(0.0731)	(0.0722)	(0.0671)	(0.0599)	(0.0342)	(0.0360)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.014	0.090	0.115**	-0.017	0.091	-0.061	-0.080	-0.063*	-0.047
	(0.017)	(0.115)	(0.056)	(0.074)	(0.095)	(0.075)	(0.063)	(0.033)	(0.038)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes. Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10. . Subgroups were constructed by restricting the sample to those who moved into automatable work (Row 1) and those who moved into non-automatable work (Row 2).
**** p<0.01, ** p<0.05, * p<0.1*

The findings outlined **are** robust to the inclusion of a range of additional controls, including income, marital status, race, socio-economic disadvantage and age (Appendix 5.1); and age and age squared (*Appendix 5.2*); hours worked, income per hour worked and tenure in role (*Appendix 5.3*), as well as the inclusion of area-by-time fixed effects (*Appendix 5.4*) and exclusion of individual fixed effects (*Appendix 5.8*). The findings **are also** robust across the OLS models (*Appendix 5.9*). Although using a continuous rather than binary variable to classify automatability generally reduced the estimated size of the effect, the findings **are** robust across most of the specifications for the pooled samples across industries (*Appendix 5.7*).

Conclusion

This study had three key objectives. First, it sought to explore possible associations of exposure to job automation risk on mental health and life satisfaction. Second, it aimed to identify whether workers across different demographic groups are disproportionately impacted by such associations. Finally, it aimed to identify particular aspects of health and life satisfaction which are associated with working in an automatable occupation, and thus, may influence mental health and life satisfaction. In doing so, we utilised Autor and Dorn (2013)'s classification of automatable work, which classifies job automation risk according to a measure of RTI. Using the HILDA panel dataset, we followed the empirical approach of Lordan and Neumark (2018) to explore the effect of job automation risk on mental health and life satisfaction in Australia from 2001 to 2019.

Although we find no associations across the full workforce sample, we find evidence of small, detrimental associations on mental health and life satisfaction within several industries, particularly those with high levels of job automation risk, with the notable

Table 71. Effect of Working in an Automatable Occupation on SF-36 Health Domains

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample	0.015	-0.033**	0.064	0.005	-0.004	-0.025*	0.0089	0.025*
	(0.014)	(0.014)	(0.175)	(0.016)	(0.015)	(0.014)	(0.016)	-0.013
N	41,900	41,544	57,791	41,585	41,583	41,657	41,899	41,894

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Each column reports the results of each of the eight SF-36 Health Domains (Mental Health, Physical Health, General Health, Role Functioning (Emotions), Role Functioning (Physical), Bodily Pain, Social Function, Vitality) across the aggregated sample. The model controls for individual, time and area fixed effects.
**** p<0.01, ** p<0.05, * p<0.1*

Table 8. Effect of Working in an Automatable Occupation on Life Satisfaction Measures

	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample	0.004	-0.010	-0.059***	-0.026*	-0.009	-0.013	-0.010	-0.006	0.071***
	(0.014)	(0.016)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.016)
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896	41,876	41,888

Notes. Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Each column reports the results of each of the nine measures of life satisfaction collected by the HILDA survey (Life Satisfaction, Satisfaction with Home, Employment Opportunities, Financial Situation, Safety, Local Community, Health, Neighbourhood, Free Time) across the aggregated sample. The model controls for individual, time and area fixed effects.
**** p<0.01, ** p<0.05, * p<0.1*

exception of the services industry, in which the effect was positive. This pattern is particularly apparent when looking at the direction of movement between automatable and non-automatable occupations. Specifically, a move to an automatable occupation is associated with reduced mental health and life satisfaction, while a move to a non-automatable occupation with a higher mental health and life satisfaction, except in the case of the services industry. Considering that the services industry is the only industry which has not seen declining employment opportunities for lower-skilled workers, this finding suggests that job insecurity may act as a mediator of job automation risk on life satisfaction (Autor & Dorn, 2013). Further, we find evidence of heterogeneous associations by age, gender and education level, including more significant associations among women in the construction industry, and the youngest workers in the retail industry.

The majority of results observed were robust to a variety of model specifications. Overall, this study provides further evidence that job automation risk has a negative effect on mental health and life satisfaction. However, our estimates also suggest that people adapt to any deteriorating impacts on mental health and life satisfaction within one year. This implies a limited role for firm policy beyond ensuring a one-year retention.

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Appendices for
People versus machines: The impact of being in an automatable job on worker's mental health and wellbeing

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****** For online publication only ******

Appendices

Appendix 1. Top 5 Automatable and Non-Automatable Occupations (by share of employment)

Industry	Top 5 Automatable Occupations	Top 5 Non-automatable Occupations
Construction	1. Numerical Clerks 2. Office Managers and Program Administrators 3. Personal Assistants and Secretaries 4. Machine and Stationary Plant Operators 5. General Clerical Clerks	1. Construction Trades Workers 2. Electrotechnology and Telecommunications 3. Construction and Mining Labourers 4. Specialist Managers 5. Mobile Plant Operators
Manufacturing	1. Factory Process Workers 2. Machine and Stationary Plant Operators 3. Numerical Clerks 4. Other Clerical and Administrative Workers 5. Office Managers and Program Administrators	1. Automotive and Engineering Trades 2. Specialist Managers 3. Other Technicians and Trades Workers 4. Design, Engineering, Science and Transport Professionals 5. Engineering, ICT and Science Technicians
Transport	1. Clerical and Office Support Workers 2. Other Clerical and Administrative Workers 3. General Clerical Workers 4. Numerical Clerks 5. Office Managers and Program Administrators	1. Road and Rail Drivers 2. Specialist Managers 3. Other Labourers 4. Hospitality, Retail and Service Managers 5. Storepersons
Wholesale	1. Sales Representatives and Agents 2. Other Clerical and Administrative Workers 3. Numerical Clerks 4. General Clerical Workers 5. Office Managers and Program Administrators	1. Specialist Managers 2. Business, Human Resource and Marketing Professionals 3. Road and Rail Drivers 4. Storepersons 5. Sales Assistants and Salespersons
Retail	1. Numerical Clerks 2. Other Clerical and Administrative Workers 3. Cleaners and Laundry Workers	1. Sales Assistants and Salespersons 2. Hospitality, Retail and Service Managers 3. Sales Support Workers

	4. General Clerical Workers 5. Sales Representatives and Agents	4. Other Labourers 5. Specialist Managers
Finance	1. Numerical Clerks 2. Sales Representatives and Agents 3. Inquiry Clerks and Receptionists 4. General Clerical Workers 5. Office Managers and Program Administrators	1. Business, Human Resource and Marketing Professionals 2. Specialist Managers 3. Hospitality, Retail and Service Managers 4. ICT Professionals 5. Sales Assistants and Salespersons
Services	1. Legal, Social and Welfare Professionals 2. Inquiry Clerks and Receptionists 3. Numerical Clerks 4. Office Managers and Program Administrators 5. General Clerical Workers	1. Health Professionals 2. Carers and Aides 3. Specialist Managers 4. Health and Welfare Support Workers 5. Hospitality, Retail and Service Managers
Public Administration	1. Cleaners and Laundry Workers 2. Other Clerical and Administrative Workers 3. General Clerical Workers 4. Office Managers and Program Administrators 5. Inquiry Clerks and Receptionists	1. Education Professionals 2. Specialist Managers 3. Business, Human Resource and Marketing Professionals 4. Protective Service Workers 5. Carers and Aides

Notes: Data from HILDA 18th Release. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code.

Appendix 2. *Crosswalk for ANZSCO 2006 Occupation Classification Codes to those used by Autor and Dorn (2013), and the Corresponding Automatability Classification*

Occupation Codes	**Corresponding Occupations by Autor and Dorn (2013)**	**Automatability Classification**	
		Binary	**Continuous**
[10] Managers	[4] Chief executives, public administrators, and legislators	Non-Automatable	-0.508
[11] Chief Executives, General Managers	[22] Managers and administrators, n.e.c.	Non-Automatable	-0.539
[12] Farmers and Farm Managers	Farmers (owners and tenants) Farm managers [47Farm workers, incl. nursery farming	Automatable	4.933
[13] Specialist Managers	[7] Financial managers Human resources and labour relations managers Managers and specialists in marketing, advert., PR Managers in education and related fields Managers of medicine and health occupations Managers of properties and real estate	Non-Automatable	2.057
[14] Hospitality, Retail and Service Managers	[433] Supervisors of food preparation and service Supervisors of cleaning and building service Supervisors of landscaping, lawn service, groundskeeping Supervisors of personal service jobs, n.e.c Supervisors of construction work	Non-Automatable	0.834

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
[21] Arts and Media Professionals	Technical writers Designers Musicians and composers Actors, directors, and producers Painters, sculptors, craft-artists, and print-makers Photographers Dancers [194]Art/entertainment performers and related occupations	Non-Automatable	-0.313
[22] Business, Human Resource and Marketing Professionals	Business and promotion agent [13] Managers and specialists in marketing, advert., P	Non-Automatable	0.897
[23] Design, Engineering, Science and Transport Professionals	Aerospace engineers Metallurgical and materials engineers Petroleum, mining, and geological engineers Chemical engineers Civil engineers Electrical engineers Industrial engineers Mechanical engineers [59] Engineers and other professionals, n.e.c	Non-Automatable	-0.238

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
[24] Education Professionals	[154] Kindergarten and earlier schoolteachers Primary school teachers Secondary school teachers Special education teachers Teachers, n.e.c	Non-Automatable	-0.242
[25] Health Professionals	[84] Physicians Dentists Podiatrists Other health and therapy occupations Registered nurses Pharmacists Speech therapists Therapists, n.e.c. Physicians' assistants	Non-Automatable	-1.081
[26] ICT Professionals	[229] Computer software developers Programmers of numerically controlled machine tool	Non-Automatable	-0.028
[27] Legal, Social and Welfare Professionals	Legal assistants and paralegal [178] Lawyers and judges	Automatable	3.349
[30] Technicians and Trades Workers	Mason, tilers and carpet installers [567] Carpenters	Non-Automatable	-.2910

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
	Drywall installers Electricians Painters, construction and maintenance Paperhangers Plasterers Plumbers, pipe fitters and steamfitters		
[31] Engineering, ICT and Science Technicians	[214] Engineering technicians Surveyors, cartographers, mapping scientists/techs Biological technicians Chemical technicians Other science technicians	Non-Automatable	0.529
[32] Automotive and Engineering Trades	[503] Supervisors of mechanics and repairers Repairers of data processing equipment Millwrights Electric power installers and repairers Automobile mechanics and repairers Bus, truck and stationary engine mechanics Aircraft mechanics Small engine repairers	Non-Automatable	-0.195

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	Continuous
[33] Construction Trades Workers	Concrete and cement Glaziers Insulation workers Paving, surfacing and tamping equipment operators Roofers and slaters [599] Misc. construction and related occupations	Non-Automatable	0.525
[34] Electrotechnology and Telecommunications	[228] Broadcast equipment operators	Non-Automatable	1.039
[35] Food Trades Workers	[686] Butchers and meat cutters Bakers Batch food makers	Automatable	5.680
[36] Skilled Animal and Horticultural Workers	[472] Animal caretakers, except farm	Non-Automatable	1.471
[39] Other Technicians and Trades Workers	Drillers of earth Drillers of oil wells Explosive workers Miners Other mining occupations Production supervisors of foremen [657] Cabinetmakers and bench carpenters	Non-Automatable	0.120

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
	Dressmakers, seamstresses and tailors Upholsterers Shoemakers, other prec. Apparel and fabric workers		
[41] Health and Welfare Support Workers	[174] Social workers Clergy and religious workers Welfare service workers	Non-Automatable	0.698
[42] Carers and Aides	[95] Registered nurses	Non-Automatable	-0.121
[43] Hospitality Workers	[435] Waiters and waitresses Food preparation workers Miscellaneous food preparation and service workers	Non-Automatable	-0.633
[44] Protective Service Workers	Supervisors of guards Fire fighting, fire prevention, and fire inspection occs Police and detectives, public service Sheriffs, bailiffs, correctional institution officers	Non-Automatable	-0.366

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
	Crossing guards [427] Protective service, n.e.		
[45] Sports and Personal Service Worker	[199] Athletes, sports instructors, and officials	Non-Automatable	-2.231
[50] Clerical and Administrative Worker	[364] Shipping and receiving clerks Stock and inventory clerks Weighers, measurers, and checkers Material recording, sched., prod., plan., expediting clerks	Automatable	2.332
[51] Office Managers and Program Administrators	Insurance adjusters, examiners, and investigators Customer service reps, invest., adjusters, excl. insurance Eligibility clerks for government prog., social welfare [378] Bill and account collectors	Automatable	3.815
[52] Personal Assistants and Secretaries	[389] Administrative support jobs, n.e.c	Automatable	3.781
[53] General Clerical Workers	[379] General office clerks File clerks Records clerks	Automatable	3.916
[54] Inquiry Clerks and Receptionists	[319] Receptionists and other information clerks Transportation ticket and reservation agents	Automatable	3.975

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
[55] Numerical Clerks	[385] Data entry keyers Statistical clerks Bill and account collectors	Automatable	2.797
[56] Clerical and Office Support Worker	[313] Secretaries and stenographers Typists Correspondence and order clerk	Automatable	5.655
[59] Other Clerical and Administrative	[389] Administrative support jobs, n.e.c	Automatable	3.781
[60] Sales Workers	[274] Salespersons, n.e.c	Non-Automatable	1.327
[61] Sales Representatives and Agents	Door-to-door sales, street sales, and news vendors [254] Real estate sales occupation Financial service sales occupation	Automatable	2.498
[62] Sales Assistants and Salespersons	[275] Retail salespersons and sales clerk	Non-Automatable	0.855
[63] Sales Support Workers	[283] Sales demonstrators, promoters, and models	Non-Automatable	0.537
[70] Machinery Operators and Drivers	[779] Machine operators, n.e.c	Non-Automatable	1.030
[71] Machine and Stationary Plant Operators	Lathe, milling, and turning machine operative Drilling and boring machine operator Grinding, abrading, buffing, and polishing worker Molders and casting machine operators	Automatable	2.427

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
	Metal platers Nail, tacking, shaping and joining mach ops (wood) Other woodworking machine operators Printing machine operators, n.e.c. Typesetters and compositors Winding and twisting textile and apparel operatives Knitters, loopers, and toppers textile operatives Textile cutting and dyeing machine operator [749] Miscellaneous textile machine operator Cementing and gluing machine operator Extruding and forming machine operator Mixing and blending machine operators Food roasting and baking Washing, cleaning, and pickling machine operator Paper folding machine operator Slicing, cutting, crushing and grinding machine Photographic process workers		
[72] Mobile Plant Operators	[853] Excavating and loading machine operators Stevedores and misc. material moving occupations Crane, derrick, winch, hoist, longshore operators	Non-Automatable	0.499

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	**Continuous**
[73] Road and Rail Drivers	[804] Truck, delivery, and tractor drivers Bus drivers Taxicab drivers and chauffeurs	Non-Automatable	-0.5552
[74] Storepersons	[275] Retail salespersons and sales clerk	Non-Automatable	0.855
[80] Labourers	[889] Laborers, freight, stock, and material handlers, n.e.c.	Non-Automatable	0.812
[81] Cleaners and Laundry Workers	[887] Vehicle washers and equipment cleaners	Automatable	1.715
[82] Construction and Mining Labourers	[869] Construction laborers	Non-Automatable	0.665
[83] Factory Process Workers	[799] Production checkers, graders, and sorters in manufacturing Packers and packagers by hand Production helpers	Automatable	1.947
[84] Farm, Forestry and Garden Workers	[451] Gardeners and groundskeepers	Non-Automatable	0.093
[85] Food Preparation Assistants	[439] Food preparation workers Miscellaneous food preparation and service worker	Non-Automatable	1.000
[89] Other Labourers	[859] Stevedores and misc. material moving occupation Helpers, constructions	Non-Automatable	0.067

Occupation Codes	Corresponding Occupations by Autor and Dorn (2013)	Automatability Classification	
		Binary	Continuous
	Helpers, surveyors Garbage and recyclable material collector Machine feeders and offbearers		

Notes: Data from HILDA 18th Release. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code.

Appendix 3. Exclusions Specifications

Sample Population Exclusion Specifications

Exclusion Specifications	**# of Observations**
Raw Dataset	364,427
Restriction to those who responded across each wave	104,508
Omit missing and non-numeric (i.e. prefer not to say) observations for outcome variables (SF36 and life satisfaction)	99,061
Omit variables for industries which don't map to Autor & Dorn's work (*Agriculture, Forestry & Fishing, Mining, Electricity, Gas and Water Wate & Other Services)*	58,162
Restrict to those who stay in the same industry	41,923

Appendix 4. Descriptive Statistics

4a) Descriptive Statistics for Key Outcome Variables (Mental Health and Life Satisfaction)

	Aggregated Sample			Automatable Occupations			Non-Automatable Occupations		
	N	Mean	Std Dev.	N	Mean	Std Dev.	N	Mean	Std Dev.
SF-36 Health Domains (standardised)									
Mental Health	41,923	2.62e-09	1.000	10,420	-.0049	1.009	31,503	0.02	0.996
Role-emotional	41,608	6.73e-09	1.000	10,343	-0.008	1.007	31,265	-0.003	0.997
Social Functioning	41,922	-8.80e-09	1.000	10,419	-0.019	1.027	31,503	0.007	0.991
Vitality	41,917	1.37e-08	1.000	10,418	0.006	1.007	31,499	-0.001	0.997
General Health	41,708	6.59e-09	1.000	10,347	0.007	1.016	31,347	-0.002	0.994
Bodily Pain	41,680	5.50e-09	1.000	10,362	-0.016	1.020	31,318	0.005	0.993
Physical Functioning	41,567	-1.44e-08	1.000	10,334	-0.075	1.091	31,233	0.024	0.966
Role- physical	41,606	-4.57e-09	1.000	10,343	-0.006	0.998	31,263	-0.002	1.000
Life Satisfaction Domains (standardised)									
Satisfaction with Home	41,923	-2.44e-09	1.000	10,420	-0.016	1.014	31,503	-0.005	0.995
Employment Opportunities	41,170	8.99e-10	1.000	10,200	-0.147	1.044	30,970	0.048	0.980
Financial Situation	4,921	1.31e-08	1.000	10,419	-0.049	1.016	31,502	0.016	0.994
Safety	41,914	-5.77e-09	1.000	10,418	-0.087	-0.087	31,496	0.028	0.988
Part of the Local Community	41,890	-2.06e-09	1.000	10,413	-0.059	-0.059	31,477	0.019	0.992
Satisfaction with health	41,919	4.02e-09	1.000	10,419	-0.015	1.015	31,500	0.005	0.994
Neighbourhood	41,899	8.25e-09	1.000	10,414	-0.045	1.042	31,485	0.014	0.984

Amount of free time	41,911	-5.41e-09	1.000	10,417	-0.018	0.996	31,494	-0.018	1.001

Notes. Data from HILDA 18th Release with own analysis and illustration. Means displayed (proportions in the case of binary variables).

4b) Descriptive Statistics for Demographic Groups

	Aggregated Sample		Automatable Occupations		Non-Automatable Occupations	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Primary Outcome Variables						
Mental Health (SF-36) - Standardised	-2.62e-09	1.000	-0.005	1.009	0.002	0.996
Life Satisfaction (Standardised)	-2.44e-09	1.000	-0.016	1.013	0.005	0.993
Age	46.216	11.244	47.356	11.029	44.912	11.288
Gender (Male =1)	1.524	0.500	1.523	0.463	1.469	0.499
Highest Level of Education Attained						
No non-school qualifications	0.323	0.467	0.510	0.500	0.261	0.439
Certificate or Diploma	0.333	0.471	0.276	0.447	0.353	0.478
Bachelor's Degree or Post-Graduate Qualification	0.322	0.467	0.204	0.403	0.364	0.481
N	41,913		10,417		31,496	

Notes. Data from HILDA 18th Release with own analysis and illustration. Means displayed (proportions in the case of binary variables).

Appendix 5. *Robustness Checks*

5.1 Robustness Check with Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status)

a) Robustness Check with Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status): Pooled Sample and by Industry

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable Occupation	0.013	0.171***	0.083*	0.144***	-0.096*	0.161***	-0.018	-0.040	-0.006
	(0.0136)	(0.0593)	(0.0415)	(0.0358)	(0.0545)	(0.0583)	(0.0617)	(0.0256)	(0.0298)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	0.001	-0.028	0.043	0.040	0.083	-0.113**	-0.056	-0.035	-0.064***
	(0.016)	(0.072)	(0.036)	(0.056)	(0.060)	(0.052)	(0.043)	(0.032)	(0.023)
N	41,900	2,834	5,836	2,115	1,101	3,306	2,281	15,147	11,059

Notes. Estimates of Eq. (2) are reported, with the inclusion of additional controls (income, marital status, race, socio-economic disadvantage and age). Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10.

*** p<0.01, ** p<0.05, * p<0.1

b) Additional Controls (Education, Age, Income, Marital Status, Race and SES): Mental Health by Pooled Sample and Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
					Age Group				
15-39 years									
Automatable	-0.0555**	0.133*	-0.0355	0.0178	-0.426***	0.0244	-0.0156	-0.0752	-0.0426
Occupation	(0.0267)	(0.0683)	(0.0577)	(0.104)	(0.134)	(0.0919)	(0.119)	(0.0608)	(0.0798)
N	11,499	887	1,275	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	0.0410**	0.197***	0.0728	0.139***	-0.0680	0.164**	-0.0135	0.00403	-0.00816
Occupation	(0.0162)	(0.0695)	(0.0570)	(0.0411)	(0.0559)	(0.0759)	(0.0482)	(0.0282)	(0.0387)
N	30,401	1,947	2,782	1,712	859	1,967	1,582	10,900	8,652
					Gender				
Males									
Automatable	0.0146	0.148**	0.0333	0.130***	-0.127*	0.0853	0.0430	0.0620	-0.0599
Occupation	(0.0174)	(0.0617)	(0.0423)	(0.0473)	(0.0706)	(0.0935)	(0.0471)	(0.0389)	(0.0396)
N	19,963	2,514	3,120	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.00964	0.396**	0.287***	0.177	-0.0517	0.179**	-0.0483	-0.0780**	0.0220
Occupation	(0.0191)	(0.181)	(0.0849)	(0.121)	(0.118)	(0.0793)	(0.0834)	(0.0299)	(0.0415)
N	21,937	320	937	506	363	2,000	1,204	10,000	6,607
					Highest Level of Education Attained				
High School or Below									
Automatable	0.000666	0.114	0.0671	0.201***	-0.179*	0.121	-0.0764	0.00740	0.0119
Occupation	(0.0211)	(0.0820)	(0.0615)	(0.0465)	(0.0923)	(0.0905)	(0.0856)	(0.0385)	(0.0579)
N	13,538	947	1,647	1,262	552	1,967	847	4,156	2,160
Diploma or Certific									
Automatable	0.0740***	0.254**	0.0812	0.0578	0.138	0.0887	0.131	0.0812*	-0.0117
Occupation	(0.0256)	(0.102)	(0.0589)	(0.0997)	(0.0924)	(0.124)	(0.119)	(0.0437)	(0.0520)
N	14,163	1,617	1,814	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.0167	0.424**	0.261**	-0.298	-0.170	0.223*	-0.0375	-0.143***	-0.00271
Occupation	(0.0284)	(0.157)	(0.122)	(0.280)	(0.153)	(0.117)	(0.0821)	(0.0476)	(0.0452)
N	14,199	270	596	157	252	402	837	6,044	5,641

Notes. See Notes to Table 3.1a).

c) Additional Controls (Education, Age, Income, Marital Status, Race and SES): Life Satisfaction by Pooled Sample and Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Age Group									
15-39 years									
Automatable	-0.0292	-0.0510	-0.0746	-0.150	0.285***	-0.280***	0.0268	0.0347	-0.0760
Occupation	(0.0296)	(0.172)	(0.0826)	(0.136)	(0.0737)	(0.0828)	(0.0713)	(0.0513)	(0.0739)
N	11,499	887	1,999	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	-0.00125	-0.0452	0.0137	0.0102	0.0547	-0.0535	-0.120**	-0.0315	-0.0519
Occupation	(0.0186)	(0.0457)	(0.0431)	(0.0411)	(0.0791)	(0.0595)	(0.0531)	(0.0378)	(0.0322)
N	30,401	1,947	3,837	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	0.0146	-0.0529	0.0346	0.0260	0.0442	-0.122	-0.00538	-0.0177	-0.0814*
Occupation	(0.0174)	(0.0809)	(0.0321)	(0.0388)	(0.0645)	(0.0990)	(0.0494)	(0.0430)	(0.0445)
N	19,963	2,514	4,324	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.00964	0.227**	0.0889	0.132	0.121	-0.171***	-0.0766	-0.0408	-0.0566*
Occupation	(0.0191)	(0.100)	(0.0895)	(0.160)	(0.127)	(0.0495)	(0.0593)	(0.0429)	(0.0323)
N	21,937	320	1,512	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
High School or Below									
Automatable	-0.0476*	-0.179	-0.0275	0.0495	0.00687	-0.193**	0.0248	-0.0144	-0.0841
Occupation	(0.0267)	(0.136)	(0.0510)	(0.0801)	(0.0638)	(0.0782)	(0.0345)	(0.0498)	(0.0594)
N	13,538	947	2,418	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.0783**	0.0190	0.146***	-0.0193	0.406***	-0.111	-0.122	0.0323	-0.0406
Occupation	(0.0307)	(0.0815)	(0.0469)	(0.135)	(0.102)	(0.0755)	(0.0873)	(0.0575)	(0.0693)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.0281	0.311***	-0.0862	0.315**	-0.162	-0.0774	-0.0698	-0.102**	-0.0559*
Occupation	(0.0221)	(0.0957)	(0.102)	(0.137)	(0.132)	(0.136)	(0.0455)	(0.0437)	(0.0317)
N	14,199	270	904	157	252	402	837	6,044	5,641

Notes: See Notes to Table 3.1a).

d) Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status): SF-36 Health Domain

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample								
Automatable Occupation	0.0131	-0.0328**	0.0684	0.00211	-0.00391	-0.0241	0.00624	0.0259**
	(0.0136)	(0.0142)	(0.237)	(0.0147)	(0.0161)	(0.0148)	(0.0154)	(0.0128)
N	41,900	41,544	41,685	41,585	41,583	41,657	41,899	41,894

Notes: See Notes to Table 3.1a).

e) Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status): Life Satisfaction Domains, by Industry

	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample									
Automatable Occupation	0.000560	-0.00664	-0.0572***	-0.0264*	-0.00916	-0.0132	-0.00963	-0.00129	0.0724***
	(0.0158)	(0.0169)	(0.0197)	(0.0146)	(0.0139)	(0.0135)	(0.0150)	(0.0154)	(0.0170)
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896	41,876	41,888

Notes: See Notes to Table 3.1a).

f) Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status): Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Move to automatable job									
Automatable Occupation	0.0180	0.0818	0.0777*	0.166***	-0.0612	0.125*	0.0150	-0.0302	0.0128
	(0.0146)	(0.0539)	(0.0435)	(0.0500)	(0.0606)	(0.0643)	(0.0549)	(0.0314)	(0.0327)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.00938	0.302***	0.136**	0.170***	-0.108	0.299***	-0.0838	-0.115***	0.0104
	(0.0174)	(0.102)	(0.0559)	(0.0375)	(0.0759)	(0.0555)	(0.0769)	(0.0308)	(0.0401)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

g) Additional Controls (Education, Age, Income, Marital Status, Race and Socio-Economic Status): Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Move to automatable job									
Automatable	-0.00712	-0.0700	0.0564	0.0179	0.0307	-0.148**	-0.0374	-0.0328	-0.0910***
Occupation	(0.0172)	(0.0815)	(0.0488)	(0.0665)	(0.0640)	(0.0563)	(0.0538)	(0.0354)	(0.0279)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.00804	0.131*	0.117**	0.000487	0.110	-0.0653	-0.0801	-0.0685**	-0.0479
	(0.0189)	(0.0742)	(0.0468)	(0.0789)	(0.0899)	(0.0674)	(0.0633)	(0.0324)	(0.0382)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

5.2 Robustness Check: Regressions with Additional Controls (Age and Age Squared)

a) Regressions with Additional Controls (Age and Age Squared): Pooled Samples and by Industry

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable Occupation	0.014	0.154**	0.079*	0.151***	-0.094*	0.174***	-0.020	-0.040	-0.014
	(0.013)	(0.059)	(0.042)	(0.033)	(0.054)	(0.056)	(0.062)	(0.026)	(0.029)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	0.004	-0.064	0.078*	0.017	0.064	-0.105**	-0.069*	-0.032	-0.071***
	(0.016)	(0.073)	(0.044)	(0.051)	(0.069)	(0.046)	(0.040)	(0.034)	(0.020)
N	41,900	2,834	5,836	2,115	1,101	3,306	2,281	15,147	11,059

Notes. Estimates of Eq. (2) are reported, with the inclusion of additional controls (age and age squared). Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-100.
*** p<0.01, ** p<0.05, * p<0.1

b) FE Model with Additional Controls (Age and Age Squared): Mental Health on Aggregated Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Age Group									
15-39 years									
Automatable	-0.049*	0.149*	-0.043	0.020	-0.407***	0.022	-0.014	-0.071	-0.037
Occupation	(0.026)	(0.074)	(0.057)	(0.103)	(0.134)	(0.089)	(0.118)	(0.061)	(0.075)
N	11,499	887	1,275	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	0.038**	0.197***	0.071	0.139***	-0.067	0.192**	-0.0301	0.001	-0.010
Occupation	(0.016)	(0.067)	(0.057)	(0.040)	(0.054)	(0.076)	(0.045)	(0.027)	(0.039)
N	30,401	1,947	2,782	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	0.016	0.125*	0.033	0.137***	-0.123*	0.096	0.046	0.067*	-0.063
Occupation	(0.017)	(0.062)	(0.044)	(0.046)	(0.067)	(0.089)	(0.045)	(0.039)	(0.039)
N	19,963	2,514	3,120	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.010	0.388**	0.264***	0.180	-0.026	0.192**	-0.050	-0.080**	0.012
Occupation	(0.019)	(0.168)	(0.084)	(0.118)	(0.089)	(0.078)	(0.083)	(0.031)	(0.041)
N	21,937	320	937	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
High School or Below									
Automatable	0.001	0.094	0.062	0.219***	-0.150*	0.133	-0.0939	0.001	0.003
Occupation	(0.021)	(0.075)	(0.060)	(0.050)	(0.086)	(0.087)	(0.077)	(0.038)	(0.058)
N	13,538	947	1,647	1,262	552	1,967	847	4,156	2,160
Diploma or Certific									
Automatable	0.073***	0.230**	0.079	0.065	0.010	0.075	0.147	0.082*	-0.005
Occupation	(0.0257)	(0.102)	(0.061)	(0.079)	(0.076)	(0.124)	(0.124)	(0.041)	(0.051)
N	14,163	1,617	1,814	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.0160	0.418**	0.256*	-0.250	-0.127	0.246*	-0.0410	-0.137***	-0.0116
Occupation	(0.0289)	(0.170)	(0.126)	(0.273)	(0.125)	(0.124)	(0.0834)	(0.0485)	(0.0441)
N	14,199	270	596	157	252	402	837	6,044	5,641

Notes. See Notes to Table 3.1a).

c) FE Models with Additional Controls (Age and Age Squared): Life Satisfaction on Aggregated Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
					Age Group				
15-39 years									
Automatable	-0.019	-0.094	-0.096	-0.198	0.297***	-0.306***	0.049	0.034	-0.066
Occupation	(0.030)	(0.162)	(0.102)	(0.144)	(0.072)	(0.079)	(0.066)	(0.053)	(0.069)
N	11,499	887	1,999	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	-0.002	-0.048	0.059	0.009	0.037	-0.027	-0.140***	-0.031	-0.056*
Occupation	(0.018)	(0.051)	(0.045)	(0.038)	(0.086)	(0.060)	(0.048)	(0.038)	(0.031)
N	30,401	1,947	3,837	1,712	859	1,967	1,582	10,900	8,652
					Gender				
Males									
Automatable	0.016	0.125*	0.0335	0.137***	-0.123*	0.0966	0.0464	0.0677*	-0.0631
Occupation	(0.0175)	(0.0620)	(0.0442)	(0.0460)	(0.0673)	(0.0894)	(0.0457)	(0.0393)	(0.0394)
N	19,963	2,514	4,324	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.010	0.226**	0.119	0.124	0.145	-0.172***	-0.098*	-0.040	-0.065**
Occupation	(0.019)	(0.102)	(0.106)	(0.157)	(0.113)	(0.042)	(0.056)	(0.044)	(0.032)
N	21,937	320	1,512	506	363	2,000	1,204	10,000	6,607
					Highest Level of Education Attained				
High School or Below									
Automatable	-0.048*	-0.216	-0.022	0.026	-0.011	-0.184**	-0.010	-0.028	-0.094
Occupation	(0.026)	(0.141)	(0.070)	(0.076)	(0.092)	(0.072)	(0.028)	(0.051)	(0.062)
N	13,538	947	2,418	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.079**	-0.040	0.205***	-0.031	0.311**	-0.129*	-0.116	0.033	-0.041
Occupation	(0.031)	(0.092)	(0.053)	(0.117)	(0.129)	(0.070)	(0.081)	(0.058)	(0.067)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.024	0.281***	-0.046	0.358**	-0.091	-0.002	-0.078	-0.0887*	-0.067**
Occupation	(0.021)	(0.096)	(0.090)	(0.145)	(0.098)	(0.117)	(0.051)	(0.045)	(0.031)
N	14,199	270	904	157	252	402	837	6,044	5,641

Notes: See Notes to Table 3.1a).

d) Fixed Effects Model with Additional Controls (Age and Age Squared): SF-36 Health Domain

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample								
Automatable Occupation	0.014	-0.033**	0.054	0.004	-0.004	-0.025*	0.008	0.025**
	(0.013)	(0.013)	(0.236)	(0.015)	(0.016)	(0.014)	(0.015)	(0.012)
N	41,900	41,544	41,685	41,585	41,583	41,657	41,899	41,894

Notes: See Notes to Table 3.1a).

e) Fixed Effects Model with Additional Controls (Age and Age Squared): Life Satisfaction Domains, by Industry

	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample									
Automatable Occupation	0.004	-0.008	-0.059***	-0.026*	-0.009	-0.013	-0.009	-0.006	0.073***
	(0.016)	(0.017)	(0.020)	(0.015)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896	41,876	41,888

Notes: See Notes to Table 3.1a).

f) Fixed Effects Model with Additional Controls (Age and Age Squared): Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturin g	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Move to automatable job									
Automatable	0.012	0.083	0.090**	0.152***	-0.127**	0.147**	-0.0201	-0.030	-0.004
Occupation	(0.014)	(0.055)	(0.044)	(0.044)	(0.055)	(0.059)	(0.058)	(0.030)	(0.030)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable	0.013	0.208**	0.135**	0.176***	-0.109	0.317***	-0.116	-0.081***	-0.017
Occupation	(0.017)	(0.083)	(0.050)	(0.038)	(0.074)	(0.054)	(0.074)	(0.030)	(0.038)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

g) Fixed Effects Model with Additional Controls (Age and Age Squared): Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Move to automatable job									
Automatable Occupation	0.001	-0.087	0.0845*	0.063	0.076	-0.134**	-0.073	-0.035	-0.101***
	(0.017)	(0.086)	(0.048)	(0.082)	(0.071)	(0.056)	(0.046)	(0.034)	(0.027)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.003	0.079	0.066	-0.042	0.110	-0.044	-0.113*	-0.0644*	-0.0799**
	(0.018)	(0.061)	(0.059)	(0.066)	(0.086)	(0.056)	(0.061)	(0.034)	(0.036)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

5.3 Robustness Check: Regressions with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role)

a) Regressions with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role): Pooled Samples and by Industry

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable	0.0143	0.161***	0.0763*	0.161***	-0.0964*	0.161***	-0.0166	-0.0424	-0.00767
Occupation	(0.0139)	(0.0591)	(0.0433)	(0.0326)	(0.0547)	(0.0555)	(0.0600)	(0.0259)	(0.0300)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	0.002	-0.044	0.066	0.033	0.065	-0.102*	-0.060	-0.035	-0.064***
	(0.0163)	(0.0738)	(0.0408)	(0.0516)	(0.0578)	(0.0535)	(0.0385)	(0.0341)	(0.0239)
N	41,886	2,832	4,057	2,113	1,100	3,305	2,280	15,144	11,055

Notes. Estimates of Eq. (2) are reported, with the inclusion of additional controls (Hours Worked, Income per Hour Worked, Tenure in Role). Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question “How satisfied are you with your life?”, with the response on an 11 -point Likert scale, from 0-10.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

b) FE Model with Additional Controls (Hours Worked, Income per Hour, Tenure in Role): Mental Health on Pooled Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
					Age Group				
15-39 years									
Automatable	-0.047*	0.111	-0.051	0.0393	-0.433***	0.0176	-0.028	-0.077	-0.0309
Occupation	(0.0271)	(0.0710)	(0.0591)	(0.0989)	(0.147)	(0.0902)	(0.118)	(0.0607)	(0.0762)
N	11,499	887	1,275	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	0.038**	0.196***	0.069	0.146***	-0.067	0.185**	-0.022	0.0005	-0.008
Occupation	(0.0162)	(0.0675)	(0.0590)	(0.0405)	(0.0542)	(0.0703)	(0.0426)	(0.0273)	(0.0391)
N	30,401	1,947	2,782	1,712	859	1,967	1,582	10,900	8,652
					Gender				
Males									
Automatable	0.0153	0.135**	0.0272	0.154***	-0.120*	0.0854	0.0478	0.0651	-0.0625
Occupation	(0.0175)	(0.0632)	(0.0437)	(0.0443)	(0.0670)	(0.0890)	(0.0488)	(0.0396)	(0.0383)
N	19,963	2,514	3,120	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.010	0.421**	0.280***	0.168	-0.047	0.182**	-0.053	-0.0824***	0.020
Occupation	(0.0196)	(0.179)	(0.0841)	(0.120)	(0.0928)	(0.0775)	(0.0794)	(0.0304)	(0.0411)
N	21,937	320	937	506	363	2,000	1,204	10,000	6,607
					Highest Level of Education Attained				
High School or Below									
Automatable	0.002	0.090	0.057	0.218***	-0.156*	0.119	-0.084	6.10e-05	0.014
Occupation	(0.0213)	(0.0731)	(0.0603)	(0.0497)	(0.0914)	(0.0879)	(0.0838)	(0.0391)	(0.0567)
N	13,538	947	1,647	1,262	552	1,967	847	4,156	2,160
Diploma or Certifi									
Automatable	0.075***	0.249**	0.077	0.072	0.036	0.094	0.109	0.081*	-0.004
Occupation	(0.0254)	(0.106)	(0.0594)	(0.0834)	(0.0821)	(0.129)	(0.120)	(0.0435)	(0.0497)
N	14,163	1,617	1,814	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.018	0.434**	0.228*	-0.318	-0.190	0.223	-0.058	-0.139***	-0.005
Occupation	(0.0289)	(0.183)	(0.115)	(0.267)	(0.161)	(0.148)	(0.0864)	(0.0477)	(0.0446)
N	14,199	270	596	157	252	402	837	6,044	5,641

Notes. See Notes to Table 3.1a).

c) FE Models with Additional Controls (Hours Worked, Income per Hour, Tenure in Role): Life Satisfaction on Pooled Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Age Group									
15-39 years									
Automatable	-0.01	-0.133	-0.093	-0.196*	0.280***	-0.304***	0.040	0.033	-0.068
Occupation	(0.0301)	(0.169)	(0.102)	(0.106)	(0.0875)	(0.0816)	(0.0681)	(0.0522)	(0.0691)
N	11,499	887	1,999	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	-0.006	-0.042	0.051	0.008	0.028	-0.019	-0.133***	-0.035	-0.052
Occupation	(0.0186)	(0.0500)	(0.0467)	(0.0397)	(0.0751)	(0.0574)	(0.0427)	(0.0378)	(0.0323)
N	30,401	1,947	3,837	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	0.015	0.135**	0.027	0.154***	-0.120*	0.085	0.047	0.065	-0.062
Occupation	(0.0175)	(0.0632)	(0.0437)	(0.0443)	(0.0670)	(0.0890)	(0.0488)	(0.0396)	(0.0383)
N	19,963	2,514	4,324	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.0105	0.289***	0.171*	0.118	0.148	-0.160***	-0.0906*	-0.0443	-0.0547*
Occupation	(0.0196)	(0.0900)	(0.0892)	(0.161)	(0.0957)	(0.0471)	(0.0527)	(0.0443)	(0.0328)
N	21,937	320	1,512	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
High School or Below									
Automatable	-0.0507*	-0.196	-0.0289	0.0324	0.0276	-0.192**	0.0274	-0.0269	-0.0889
Occupation	(0.0267)	(0.138)	(0.0682)	(0.0786)	(0.0869)	(0.0797)	(0.0309)	(0.0520)	(0.0622)
N	13,538	947	2,418	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.079**	-0.027	0.189***	-0.019	0.309***	-0.116	-0.131	0.027	-0.034
Occupation	(0.0311)	(0.0868)	(0.0504)	(0.110)	(0.0986)	(0.0703)	(0.0783)	(0.0592)	(0.0664)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.029	0.302**	-0.058	0.262	-0.181	-0.051	-0.081	-0.088*	-0.059*
Occupation	(0.0217)	(0.108)	(0.0829)	(0.152)	(0.135)	(0.128)	(0.0524)	(0.0449)	(0.0316)
N	14,199	270	904	157	252	402	837	6,044	5,641

Notes: See Notes to Table 3.1a).

d) Fixed Effects Model with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role): SF-36 Health Domain

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample								
Automatable Occupation	0.0143	-0.0321**	0.0722	0.00572	-0.00318	-0.0247	0.00912	0.0234*
	(0.0139)	(0.0144)	(0.236)	(0.0151)	(0.0162)	(0.0150)	(0.0157)	(0.0128)
N	41,900	41,544	41,685	41,585	41,583	41,657	41,899	41,894

Notes: See Notes to Table 3.1a).

e) Fixed Effects Model with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role): Life Satisfaction Domains, by Industry

	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample									
Automatable Occupation	0.002	-0.008	-0.058***	-0.023	-0.008	-0.013	-0.009	-0.006	0.062***
	(0.0163)	(0.0174)	(0.0197)	(0.0148)	(0.0145)	(0.0142)	(0.0153)	(0.0164)	(0.0160)
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896	41,876	41,888

Notes: See Notes to Table 3.1a).

f) Fixed Effects Model with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role): Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Move to automatable job									
Automatable	0.011	0.093*	0.088*	0.166***	-0.132**	0.134**	-0.012	-0.034	0.002
Occupation	(0.0145)	(0.0552)	(0.0452)	(0.0486)	(0.0557)	(0.0609)	(0.0557)	(0.0302)	(0.0310)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable	0.013	0.221**	0.134**	0.189***	-0.113	0.304***	-0.108	-0.084***	-0.007
Occupation	(0.0172)	(0.0841)	(0.0528)	(0.0384)	(0.0756)	(0.0512)	(0.0711)	(0.0306)	(0.0391)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

g) Fixed Effects Model with Additional Controls (Hours Worked, Income per Hour Worked, Tenure in Role): Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Move to automatable job									
Automatable Occupation	-0.001	-0.060	0.070	0.088	0.077	-0.132**	-0.064	-0.039	-0.093***
	(0.017)	(0.0874)	(0.043)	(0.085)	(0.0595)	(0.0621)	(0.0464)	(0.034)	(0.027)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.001	0.105*	0.053	-0.020	0.110	-0.039	-0.101*	-0.0681**	-0.0706*
	(0.019)	(0.055)	(0.055)	(0.0654)	(0.072)	(0.062)	(0.056)	(0.034)	(0.037)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

5.4 Robustness Check: Regressions with Area by Time Fixed Effects

a) Regressions with Area by Time Fixed Effects: Pooled Samples and by Industry

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable	0.015	0.163***	0.082*	0.150***	-0.098*	0.169***	-0.014	-0.040	-0.006
Occupation	(0.0137)	(0.0594)	(0.0412)	(0.0340)	(0.0557)	(0.0575)	(0.0603)	(0.0258)	(0.0297)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	0.004	-0.042	0.079*	0.024	0.068	-0.096*	-0.058	-0.032	-0.064***
	(0.0159)	(0.0748)	(0.0422)	(0.0526)	(0.0665)	(0.0529)	(0.0401)	(0.0335)	(0.0235)
N	41,886	2,832	4,057	2,113	1,100	3,305	2,280	15,144	11,055

Notes. Estimates of Eq. (2) are reported, however using are-by-time fixed effects. Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question “How satisfied are you with your life?”, with the response on an 11 -point Likert scale, from 0-10.
*** p<0.01, ** p<0.05, * p<0.1

b) FE Model with Additional Controls Area by Time Fixed Effects: Mental Health on Pooled Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
					Age Group				
15-39 years									
Automatable	-0.047*	0.104	-0.043	0.018	-0.406***	0.020	-0.015	-0.076	-0.035
Occupation	(0.0269)	(0.0691)	(0.0590)	(0.103)	(0.128)	(0.0896)	(0.117)	(0.0609)	(0.0756)
N	-0.0471*	0.104	-0.0433	0.0187	-0.406***	0.0202	-0.0154	-0.0767	-0.0354
Over 40 years									
Automatable	0.0404**	0.195***	0.073	0.142***	-0.068	0.195**	-0.015	0.002	-0.006
Occupation	(0.0162)	(0.0689)	(0.0570)	(0.0411)	(0.0540)	(0.0800)	(0.0443)	(0.0273)	(0.0387)
N	30,401	1,947	2,782	1,712	859	1,967	1,582	10,900	8,652
					Gender				
Males									
Automatable	0.015	0.137**	0.033	0.135***	-0.124*	0.083	0.045	0.064*	-0.055
Occupation	(0.0174)	(0.0631)	(0.0439)	(0.0471)	(0.0659)	(0.0896)	(0.0485)	(0.0390)	(0.0380)
N	19,963	2,514	3,120	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.011	0.409**	0.278***	0.178	-0.046	0.202**	-0.043	-0.079**	0.021
Occupation	(0.0193)	(0.177)	(0.0791)	(0.118)	(0.0977)	(0.0803)	(0.0803)	(0.0301)	(0.0409)
N	21,937	320	937	506	363	2,000	1,204	10,000	6,607
					Highest Level of Education Attained				
High School or Below									
Automatable	0.001	0.093	0.061	0.208***	-0.143	0.126	-0.079	0.004	0.012
Occupation	(0.0212)	(0.0761)	(0.0604)	(0.0476)	(0.0853)	(0.0913)	(0.0857)	(0.0391)	(0.0578)
N	13,538	947	1,647	1,262	552	1,967	847	4,156	2,160
Diploma or Certific									
Automatable	0.075***	0.239**	0.079	0.052	0.055	0.071	0.150	0.081*	-0.005
Occupation	(0.025)	(0.107)	(0.060)	(0.093)	(0.079)	(0.123)	(0.120)	(0.043)	(0.050)
N	14,163	1,617	1,814	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.013	0.448**	0.282**	-0.255	-0.135	0.248*	-0.061	-0.138***	-0.003
Occupation	(0.029)	(0.169)	(0.122)	(0.273)	(0.119)	(0.126)	(0.080)	(0.048)	(0.045)
N	14,199	270	596	157	252	402	837	6,044	5,641

Notes. See Notes to Table 3.1a).

c) FE Models with Area by Time Fixed Effects: Life Satisfaction on Pooled Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Age Group									
15-39 years									
Automatable	-0.016	-0.104	-0.094	-0.184	0.297***	-0.304***	0.051	0.034	-0.068
Occupation	(0.0299)	(0.166)	(0.104)	(0.132)	(0.0788)	(0.0806)	(0.0659)	(0.0518)	(0.0694)
N	11,499	887	1,999	403	242	1,339	699	4,247	2,407
Over 40 years									
Automatable	-0.006	-0.042	0.051	0.008	0.028	-0.019	-0.133***	-0.035	-0.052
Occupation	(0.0186)	(0.0500)	(0.0467)	(0.0397)	(0.0751)	(0.0574)	(0.0427)	(0.0378)	(0.0323)
N	30,401	1,947	3,837	1,712	859	1,967	1,582	10,900	8,652
Gender									
Males									
Automatable	0.0156	0.137**	0.0334	0.135***	-0.124*	0.0838	0.0459	0.0646*	-0.0551
Occupation	(0.0174)	(0.0631)	(0.0439)	(0.0471)	(0.0659)	(0.0896)	(0.0485)	(0.0390)	(0.0380)
N	19,963	2,514	4,324	1,609	738	1,306	1,077	5,147	4,452
Females									
Automatable	0.011	0.228**	0.159*	0.125	0.167	-0.156***	-0.087	-0.040	-0.055*
Occupation	(0.0193)	(0.106)	(0.0845)	(0.157)	(0.113)	(0.0428)	(0.0533)	(0.0440)	(0.0324)
N	21,937	320	1,512	506	363	2,000	1,204	10,000	6,607
Highest Level of Education Attained									
High School or Below									
Automatable	-0.048*	-0.210	-0.020	0.028	0.005	-0.179**	0.016	-0.024	-0.087
Occupation	(0.0262)	(0.138)	(0.0689)	(0.0759)	(0.0885)	(0.0740)	(0.0319)	(0.0504)	(0.0611)
N	13,538	947	2,418	1,262	552	1,967	847	4,156	2,160
Diploma or Certificate									
Automatable	0.080***	-0.024	0.203***	-0.043	0.361***	-0.139*	-0.105	0.031	-0.036
Occupation	(0.0309)	(0.0836)	(0.0540)	(0.126)	(0.116)	(0.0729)	(0.0785)	(0.0580)	(0.0666)
N	14,163	1,617	2,514	696	297	937	597	4,947	3,258
University Educated									
Automatable	-0.022	0.288**	-0.032	0.334*	-0.097	0.035	-0.083	-0.088*	-0.059*
Occupation	(0.0222)	(0.104)	(0.0806)	(0.170)	(0.0898)	(0.134)	(0.0524)	(0.0453)	(0.0322)
N	14,199	270	904	157	252	402	837	6,044	5,641

Notes: See Notes to Table 3.1a).

d) Fixed Effects Model with Area by Time Fixed Effects: SF-36 Health Domain

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample								
Automatable Occupation	0.0150	-0.0329**	0.0643	0.00508	-0.00430	-0.0250*	0.00856	0.0248*
	(0.0137)	(0.0145)	(0.237)	(0.0152)	(0.0162)	(0.0149)	(0.0157)	(0.0130)
N	41,900	41,544	41,685	41,585	41,583	41,657	41,899	41,894

Notes: See Notes to Table 3.1a).

e) Fixed Effects Model with Area by Time Fixed Effects: Life Satisfaction Domains, by Industry

	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample									
Automatable Occupation	0.004	-0.009	-0.052***	-0.025	-0.009	-0.013	-0.009	-0.005	0.0714***
	(0.015)	(0.017)	(0.020)	(0.0158)	(0.014)	(0.0140)	(0.0153)	(0.016)	(0.017)
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896	41,876	41,888

Notes: See Notes to Table 3.1a).

f) Fixed Effects Model with Area by Time Fixed Effects: Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = SF-36 Mental Health									
Move to automatable job									
Automatable	0.014	0.220**	0.142***	0.175***	-0.113	0.310***	-0.104	-0.0822***	-0.005
Occupation	(0.0169)	(0.0855)	(0.0500)	(0.0400)	(0.0767)	(0.0545)	(0.0737)	(0.0302)	(0.0385)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable	0.013	0.221**	0.134**	0.189***	-0.113	0.304***	-0.108	-0.084***	-0.007
Occupation	(0.0172)	(0.0841)	(0.0528)	(0.0384)	(0.0756)	(0.0512)	(0.0711)	(0.0306)	(0.0391)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

g) Fixed Effects Model with Area by Time Fixed Effects: Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Dependant Variable = Life Satisfaction									
Move to automatable job									
Automatable Occupation	0.0013 (0.017)	-0.059 (0.0880)	0.084* (0.0451)	0.071 (0.0844)	0.081 (0.0667)	-0.126** (0.0600)	-0.060 (0.0475)	-0.036 (0.0341)	-0.093*** (0.0269)
N	40,371	2,775	3,794	2,010	1,019	3,220	2,122	14,729	10,702
Move to non-automatable job									
Automatable Occupation	0.003 (0.018)	0.110* (0.057)	0.071 (0.057)	-0.033 (0.066)	0.116 (0.082)	-0.039 (0.061)	-0.097 (0.060)	-0.0648* (0.033)	-0.070* (0.036)
N	40,465	2,774	3,814	2,024	1,021	3,226	2,154	14,729	10,723

Notes: See Notes to Table 3.1a).

5.5 Robustness Check: Outcome Variables Lagged by 1-year

a) Robustness Checks: Regressions with Outcome Variables Lagged by 1-year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Finance	Services	Public Administration
Dependant Variable = SF-36 Mental Health									
Aggregated Sample									
Automatable Occupation	-0.00828	0.00374	-0.108	0.0881	-0.159	0.00424	-0.0926	0.0678*	-0.0440
	(0.0315)	(0.0740)	(0.103)	(0.0839)	(0.132)	(0.0736)	(0.0850)	(0.0385)	(0.0447)
Dependant Variable = Life Satisfaction									
Aggregated Sample									
Automatable Occupation	-0.0225	0.0974	-0.0797	-0.0515	-0.155**	-0.0531	-0.0404	0.0638*	-0.0843
	(0.0379)	(0.0837)	(0.0965)	(0.101)	(0.0680)	(0.0816)	(0.0777)	(0.0334)	(0.0515)
N	35,757	2,430	3,375	1,795	926	2,736	1,994	12,933	9,568

Notes. Estimates of Eq. (2) are reported, with the outcome variable lagged by 1 year. Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

b) FE Model with Lagged Outcome Variable: SF-36 Mental Health Outcomes by Aggregated Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
					Age Group				
15-39 years									
Automatable	-0.0337	-0.0640	-0.0739	0.00791	-0.237	-0.0729	0.130	-0.0409	0.0109
Occupation	(0.0329)	(0.120)	(0.0490)	(0.0744)	(0.191)	(0.0979)	(0.142)	(0.0746)	(0.0787)
N	8,994	691	1,005	306	184	1,072	555	3,317	1,864
40 + years									
Automatable	0.0390***	0.113**	0.00411	0.0967	-0.123	0.0632	0.0751*	0.0247	-0.00711
Occupation	(0.0150)	(0.0531)	(0.0367)	(0.0687)	(0.0911)	(0.0716)	(0.0446)	(0.0297)	(0.0386)
N	26,763	1,675	2,432	1,479	732	1,736	1,436	9,610	8,652
					Gender				
Males									
Automatable	0.00552	0.0681	0.0172	0.144*	-0.229**	-0.0280	0.115*	-0.0196	-0.0182
Occupations	(0.0201)	(0.0500)	(0.0360)	(0.0726)	(0.103)	(0.0840)	(0.0639)	(0.0587)	(0.0517)
N	17,188	2,108	2,671	1,381	620	1,138	954	4,448	3,868
Females									
Automatable	0.0365*	0.132	0.0217	-0.0732	0.171	0.0729	0.0831	0.0130	0.0775*
Occupations	(0.0192)	(0.177)	(0.0874)	(0.133)	(0.180)	(0.0681)	(0.0779)	(0.0338)	(0.0419)
N	18,569	258	766	404	296	1,670	1,037	8,479	5,659
					Highest Level of Education Attained				
High School or Below									
Automatable	0.0119	-0.0738	-0.0302	0.116*	-0.0148	0.0328	0.00707	-0.00922	0.168**
Occupations	(0.0231)	(0.0729)	(0.0410)	(0.0611)	(0.116)	(0.0715)	(0.0676)	(0.0505)	(0.0660)
N	11,196	764	1,355	1,069	453	1,629	731	3,391	1,804
Diploma or Certificate									
Automatable	0.0451*	0.212***	0.0255	0.0406	-0.208	0.00455	0.192**	0.0464	-0.0504
Occupations	(0.0252)	(0.0683)	(0.0746)	(0.129)	(0.223)	(0.0899)	(0.0851)	(0.0413)	(0.0516)
N	12,183	1,378	1,570	586	252	812	517	4,237	2,831
University Educated									
Automatable	0.0556**	0.462***	0.232*	0.252**	-0.187	-0.0728	0.166	0.0239	0.0343
Occupations	(0.0265)	(0.140)	(0.120)	(0.123)	(0.212)	(0.113)	(0.110)	(0.0561)	(0.0449)
N	12,378	224	512	130	211	367	743	5,299	4,892

Notes: See notes for Table 3.2a).

c) FE Model with Lagged Outcome Variable: Life Satisfaction by Aggregated Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
					Age				
15-39 years									
Automatable	-0.080***	-0.229**	-0.0270	-0.0782	-0.373**	-0.150*	0.106	-0.112**	-0.121*
Occupation	(0.0310)	(0.0951)	(0.0573)	(0.100)	(0.170)	(0.0802)	(0.0808)	(0.0566)	(0.0666)
N	8,994	691	1,552	306	184	1,072	555	3,317	1,864
Over 40									
Automatable	-0.00233	-0.0279	-0.0122	-0.0910*	-0.0495	-0.0251	-0.103*	0.0373	-0.0453
Occupation	(0.0218)	(0.0633)	(0.0639)	(0.0525)	(0.0810)	(0.0675)	(0.0615)	(0.0417)	(0.0376)
N	26,763	1,675	3,311	1,479	732	1,736	1,436	9,610	7,663
					Gender				
Males									
Automatable	-0.0232	-0.0852	0.0299	-0.0118	-0.196**	0.0565	-0.0599	-0.0523	-0.0453
Occupation	(0.0231)	(0.0697)	(0.0397)	(0.0382)	(0.0861)	(0.0867)	(0.0538)	(0.0529)	(0.0508)
N	17,188	2,108	3,651	1,381	620	1,138	954	4,448	3,868
Females									
Automatable	0.001	-0.0111	0.0364	-0.218	0.0401	-0.158***	-0.00972	-0.00232	-0.0586
Occupation	(0.0243)	(0.228)	(0.0764)	(0.146)	(0.146)	(0.0566)	(0.0758)	(0.0410)	(0.0358)
N	18,569	258	1,212	404	296	1,670	1,037	8,479	5,659
					Highest Level of Education Attained				
High School or	-0.0431*	-0.0633	-0.0618	-0.0520	-0.0628	-0.0831	-0.0223	-0.0827*	0.0673
Below	(0.0250)	(0.0855)	(0.0584)	(0.0590)	(0.0930)	(0.0762)	(0.0675)	(0.0489)	(0.0693)
N	11,196	764	1,943	1,069	453	1,629	731	3,391	1,804
Diploma or	0.00762	-0.178*	0.0860*	-0.0720	-0.0559	-0.157	-0.0593	0.0354	-0.134**
Certificate	(0.0306)	(0.103)	(0.0498)	(0.113)	(0.118)	(0.107)	(0.117)	(0.0477)	(0.0602)
N	12,183	1,378	2,154	586	252	812	517	4,237	2,831
University	-0.00846	0.406*	0.0329	-0.0138	-0.113	0.0419	0.0286	0.00668	-0.0860*
Educated	(0.0303)	(0.222)	(0.113)	(0.213)	(0.128)	(0.0972)	(0.0709)	(0.0574)	(0.0493)
N	12,378	224	766	130	211	367	743	5,299	4,892

Notes: See notes for Table 3.2a).

d) Fixed Effects Model with Lagged Outcome Variable: SF-36 Health Domains

Mental Health	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role- Emotions	(5) Role- Physical	(6) Bodily Pain	(7) Social Function	(8) Vitality
Aggregated Sample								
Automatable Occupation	0.0238	0.00487	0.0844	0.0179	-0.00186	-0.00619	0.00465	0.0385***
	(0.0164)	(0.0127)	(0.237)	(0.0155)	(0.0139)	(0.0131)	(0.0146)	(0.0123)
N	32,211	40,140	40,268	40,194	40,198	40,258	40,460	40,456

Notes: See notes for Table 3.2a).

e) Fixed Effects Model with Lagged Outcome Variable: Life Satisfaction Domains

Life Satisfaction	(1) Life Satisfaction	(2) Satisfaction with Home	(3) Employment Opportunities	(4) Financial Situation	(5) Safety	(6) Local Community	(7) Health	(8) Neighbourhood	(9) Free Time
Aggregated Sample									
Automatable Occupations	0.00149	0.00673	-0.0134	0.00894	-0.0191	0.00850	-0.0109	-0.0114	0.0738***
	(0.0160)	(0.0163)	(0.0191)	(0.0158)	(0.0165)	(0.0152)	(0.0153)	(0.0163)	(0.0197)
N	40,461	40,452	39,780	40,460	40,451	40,435	40,457	40,439	40,450

Notes: See notes for Table 3.2a).

f) Fixed Effects Model with Lagged Outcome Variables: Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

SF-36 Mental Health	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finance	(8) Services	(9) Public Administration
Move to automatable job									
Automatable Occupation	0.0238	0.138***	0.00966	0.126	-0.109	-0.00823	0.141**	-0.0273	0.0289
	(0.0180)	(0.0390)	(0.0298)	(0.0758)	(0.107)	(0.0667)	(0.0540)	(0.0293)	(0.0378)
N	31,088	2,092	2,826	1,517	615	2,395	1,663	11,450	8,530
Move to non-automatable job									
Automatable Occupation	0.0221	0.138***	-0.0140	0.0356	-0.0668	-0.0471	0.134**	0.00214	0.0201
	(0.0187)	(0.0465)	(0.0332)	(0.0796)	(0.0602)	(0.0865)	(0.0621)	(0.0350)	(0.0389)
N	31,114	2,086	2,834	1,515	615	2,394	1,685	11,468	8,517

Notes: See notes for Table 3.2a).

g) Fixed Effects Model with Lagged Outcome Variables: Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Life Satisfaction	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Finance	Services	Public Administration
Move to automatable job									
Automatable Occupation	0.00825	0.0290	0.0561	-0.0312	-0.145	-0.106	-0.0710	-0.0201	-0.0701
	(0.0168)	(0.0909)	(0.0464)	(0.0532)	(0.137)	(0.0779)	(0.0668)	(0.0336)	(0.0424)
N	38,965	2,092	2,826	1,517	615	2,395	1,663	11,450	8,530
Move to non-automatable job									
Automatable Occupation	0.00910	0.00584	0.0899*	-0.0376	-0.0164	-0.0618	-0.0723	-0.0342	-0.0746**
	(0.0171)	(0.108)	(0.0477)	(0.0462)	(0.0801)	(0.0899)	(0.0739)	(0.0402)	(0.0328)
N	39,010	2,086	2,834	1,515	615	2,394	1,685	11,468	8,517

Notes: See notes for Table 3.2a).

5.6 Robustness Check: Unbalanced Panel Dataset

a) Regressions using Unbalanced Panel Dataset: Pooled Sample and by Industry

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail
Dependant Variable = SF-36 Mental Health						
Aggregated Sample						
Automatable Occupation	0.010	-0.003	0.007	0.078*	-0.023	0.054
	(0.009)	(0.0461)	(0.0264)	(0.041)	(0.038)	(0.040)
Dependant Variable = Life Satisfaction						
Aggregated Sample						
Automatable Occupation	0.004	-0.012	0.048*	0.014	0.086*	-0.064*
	(0.009)	(0.0490)	(0.028)	(0.041)	(0.044)	(0.038)
N	90,031	7,582	8,023	4,218	2,243	9,024

Notes. Estimates of Eq. (2) are reported, using the unbalanced panel dataset (rather than balanced dataset). Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-10.
*** p<0.01, ** p<0.05, * p<0.1

b) Fixed Effects Model with Lagged Outcome Variables: Life Satisfaction, Disaggregated

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Life Satisfaction	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Financ
Move to automatable job							
Automatable Occupation	0.004	-0.001	0.058*	0.0302	0.074	-0.057	-0.02
	(0.010)	(0.055)	(0.033)	(0.050)	(0.051)	(0.042)	(0.038
N	87,850	7,490	7,654	4,077	2,130	8,863	4,815
Move to non-automatable job							
Automatable Occupation	0.00562	0.00419	0.0398	0.0254	0.100*	-0.0651	-0.005
	(0.0111)	(0.0621)	(0.0354)	(0.0526)	(0.0565)	(0.0483)	(0.040
N	88,000	7,497	7,700	4,082	2,129	8,860	4,85

Notes: See notes for Table 3.2a).

by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

5.7 Robustness Check: Continuous Independent Variable

a) Regressions using Continuous Independent Automation Variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail
Dependant Variable = SF-36 Mental Health						
Aggregated Sample						
Automatable Occupation	-0.003	-0.000	0.027**	0.032***	-0.021	0.013
	(0.00322)	(0.0121)	(0.0129)	(0.0104)	(0.0185)	(0.0185)
Dependant Variable = Life Satisfaction						
Aggregated Sample						
Automatable Occupation	-0.007*	0.009	0.005	-0.002	0.003	-0.028**
	(0.003)	(0.017)	(0.013)	(0.006)	(0.024)	(0.012)
N	41,900	2,834	5,836	2,115	1,101	3,306

Notes. Estimates of Eq. (2) are reported, using a continuous rather than binary independant variable to categorise automatability, in line with Autor & Dorn's work. Standard errors are reported in parenthesis and are clustered by occupation. Column (1) reports the co-efficient on the aggregated sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by Eq. (1), combining the data from Autor and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed effects. Mental health is a standardised variable, derived from the SF-36 mental health responses in the HILDA survey. Life Satisfaction is a standardised variable, derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, from 0-100.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

b) FE Model using Continuous Automation Variable: Mental Health on Aggregated Sample and by Industry

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7) Finan
Dependant Variable = SF-36 Mental Health							
				Age Group			
15-39 years							
Automatable	-0.014**	0.0011	0.0245	-0.0168	-0.0364	0.00913	-0.08
Occupation	(0.00742)	(0.0250)	(0.0234)	(0.0134)	(0.0408)	(0.0391)	(0.05
N	11,499	887	1,275	403	242	1,339	699
Over 40 years							
Automatable	0.004	0.0165	0.022	0.041***	-0.0174	0.016	-0.028
Occupation	(0.003)	(0.014)	(0.015)	(0.013)	(0.020)	(0.021)	(0.01
N	30,401	1,947	2,782	1,712	859	1,967	1,58
				Gender			
Males							
Automatable	-0.001	-0.004	0.0112	0.0242**	-0.0456*	0.0221	-0.03
Occupation	(0.00471)	(0.0179)	(0.0147)	(0.0102)	(0.0225)	(0.0244)	(0.02
N	19,963	2,514	3,120	1,609	738	1,306	1,07
Females							
Automatable	-0.005	0.007	0.0834***	0.061***	0.018	0.003	-0.0528
Occupation	(0.00429)	(0.0154)	(0.0221)	(0.0218)	(0.0284)	(0.0313)	(0.01
N	21,937	320	937	506	363	2,000	1,20
				Highest Level of Education Attained			
High School or Below							
Automatable	-0.002	-0.003	0.018	0.048***	-0.0302	0.006	-0.039
Occupation	(0.005)	(0.014)	(0.021)	(0.0124)	(0.0320)	(0.0268)	(0.017
N	13,538	947	1,647	1,262	552	1,967	847
Diploma or Certific							
Automatable	0.008	0.012	0.044*	0.001	-0.018	0.003	-0.08
Occupation	(0.00617)	(0.0262)	(0.0230)	(0.0101)	(0.0470)	(0.0208)	(0.051
N	14,163	1,617	1,814	696	297	937	597
University Educated							
Automatable	-0.016**	-0.027	0.016	0.028	-0.012	0.051	-0.03
Occupation	(0.007)	(0.0504)	(0.046)	(0.0170)	(0.0430)	(0.0649)	(0.030
N	14,199	270	596	157	252	402	837

Notes. See Notes to Table 3.1a).

c) *FE Models using Continuous Automation Variable: Life Satisfaction on Aggregated Sample and by Industry*

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(Fin
Dependant Variable = Life Satisfaction							
				Age Group			
15-39 years							
Automatable	-0.009	0.030	-0.023	-0.045**	0.072**	-0.054**	-0.
Occupation	(0.00631)	(0.0357)	(0.0228)	(0.0207)	(0.0300)	(0.0211)	(0.0
N	11,499	887	1,999	403	242	1,339	69
Over 40 years							
Automatable	-0.008*	0.001	0.009	0.004	-0.009	-0.024*	-0.
Occupation	(0.00458)	(0.0228)	(0.0171)	(0.00592)	(0.0309)	(0.0142)	(0.0
N	30,401	1,947	3,837	1,712	859	1,967	1,5
				Gender			
Males							
Automatable	-0.009*	0.022	0.008	-0.000	-0.011	-0.005	-0.
Occupation	(0.00553)	(0.0208)	(0.0136)	(0.00598)	(0.0294)	(0.0166)	(0.0
N	19,963	2,514	4,324	1,609	738	1,306	1,0
Females							
Automatable	-0.004	-0.014	-0.003	-0.011	0.026	-0.056***	-0.
Occupation	(0.00518)	(0.0235)	(0.0210)	(0.0239)	(0.0461)	(0.0180)	(0.0
N	21,937	320	1,512	506	363	2,000	1,2
				Highest Level of Education Attained			
High School or Below							
Automatable	-0.015***	-0.022	0.001	0.0003	0.009	-0.052***	-0.
Occupation	(0.00580)	(0.0265)	(0.0188)	(0.0128)	(0.0377)	(0.0193)	(0.0
N	13,538	947	2,418	1,262	552	1,967	84
Diploma or Certificate							
Automatable	0.004	-0.009	0.022	-0.014	-0.005	0.000	-0.
Occupation	(0.00793)	(0.0293)	(0.0199)	(0.0210)	(0.0374)	(0.0182)	(0.0
N	14,163	1,617	2,514	696	297	937	59
University Educated							
Automatable	-0.012*	0.098***	-0.027	0.070	0.001	-0.019	-0.
Occupation	(0.00629)	(0.0322)	(0.0174)	(0.0877)	(0.0330)	(0.0624)	(0.0
N	14,199	270	904	157	252	402	81

Notes: See Notes to Table 3.1a).

d) *Fixed Effects Model using Continuous: SF-36 Health Domain*

	(1) Mental Health	(2) Physical Health	(3) General Health	(4) Role Functioning-Emotions	(5) Role Functioning-Physical	Bod
Aggregated Sample						
Automatable Occupation	0.002	-0.013*	0.063	0.003	-0.004	-0.
	(0.00941)	(0.00798)	(0.196)	(0.0104)	(0.00958)	(0.0
N	41,900	41,544	41,685	41,585	41,583	41

Notes: See Notes to Table 3.1a).

e) Fixed Effects Model using Continuous Automation Variable: Life Satisfaction Domains, by Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Life Satisfaction	Satisfaction with Home	Employment Opportunities	Financial Situation	Safety	Local Community	Health
Aggregated Sample							
Automatable Occupation	-0.006*	-0.001	-0.004	0.003	0.0009	-0.000	0.010**
	(0.00376)	(0.00452)	(0.00474)	(0.00525)	(0.00396)	(0.00413)	(0.0038
N	41,900	41,890	41,148	41,898	41,891	41,867	41,896

Notes: See Notes to Table 3.1a).

f) Fixed Effects Model using Continuous Automation Variable: Mental Health, Disaggregated by Movement Direction (to Automatable Occupation or to Non-

	(1)	(2)	(3)	(4)	(5)	(6)	(
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Fin
Dependant Variable = SF-36 Mental Health							
Move to automatable job							
Automatable Occupation	-0.003	-0.013	0.025*	0.039***	-0.014	0.007	-0.05
	(0.00340)	(0.00939)	(0.0143)	(0.00981)	(0.0196)	(0.0191)	(0.0
N	40,371	2,775	3,794	2,010	1,019	3,220	2,
Move to non-automatable job							
Automatable Occupation	-0.004	-0.008	0.034**	0.032***	-0.027	0.013	-0.06
	(0.00373)	(0.0135)	(0.0153)	(0.0101)	(0.0173)	(0.0196)	(0.0
N	40,465	2,774	3,814	2,024	1,021	3,226	2,

Notes: See Notes to Table 3.1a).

Automatable Occupation)

g) Fixed Effects Model using Continuous Automation Variable: Life Satisfaction, Disaggregated by Movement Direction (to Automatable Occupation or to Non-Automatable Occupation)

	(1)	(2)	(3)	(4)	(5)	(6)	(
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail	Fin
Dependant Variable = Life Satisfaction							
Move to automatable job							
Automatable Occupation	-0.009**	0.004	-0.006	-0.009	-0.013	-0.0356**	-0.
	(0.00381)	(0.0173)	(0.0131)	(0.00837)	(0.0206)	(0.0157)	(0.0
N	40,371	2,775	3,794	2,010	1,019	3,220	2,
Move to non-automatable job							
Automatable Occupation	-0.006	0.017	-0.001	-0.009	0.001	-0.021	-0.
	(0.00429)	(0.0216)	(0.0152)	(0.0116)	(0.0290)	(0.0135)	(0.0
N	40,465	2,774	3,814	2,024	1,021	3,226	2,

Notes: See Notes to Table 3.1a).

5.8 OLS Models

a) Effect of Working in an Automatable Occupation on Mental Health by Aggregated Sample and Industry using OLS Regressio**ns**

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Construction	Manufacturing	Transport	Wholesale	Retail
Dependant Variable = SF-36 Mental Health						
Aggregated Sample						
Automatable occupation	-0.017	0.001	-0.096	0.083	-0.142	0.118**
	(0.031)	(0.074)	(0.103)	(0.094)	(0.095)	(0.056)
Dependant Variable= Life Satisfaction						
Aggregated Sample						
Automatable occupation	-0.013	0.075	-0.090	-0.026	-0.070	-0.047
	(0.031)	(0.088)	(0.088)	(0.118)	(0.067)	(0.090)
N	58,126	2,834	4,057	2,115	1,101	3,306

Notes: OLS coefficient estimates with standard errors in parenthesis. The standard errors are clustered by occupation. Column (1) while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as shown by (2013) with the two-digit ANZSCO occupation classification code. Year and area dummies are included in the OLS model. Ment variable, derived from the SF-36 mental health responses in the HILDA survey.
*** p<0.01, ** p<0.05, * p<0.1

5.9 Disaggregation by Additional Factors

a) Disaggregated Effects of Working in an Automatable Occupation on Mental Health (SF-36) by Income and Labour Union Status

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7 Fina
Dependant Variable = SF-36 Mental Health							
				Income Tercile			
Low Income							
Automatable	0.070***	0.003	-0.060	0.301**	0.128	0.011	0.0
Occupation	(0.024)	(0.180)	(0.094)	(0.134)	(0.097)	(0.127)	(0.0
N	12,043	1,102	757	507	207	1,627	43
Middle Income							
Automatable	-0.012	0.303***	0.104**	0.147*	-0.227**	0.238***	-0.0
Occupation	(0.026)	(0.056)	(0.051)	(0.084)	(0.098)	(0.087)	(0.0
N	15,775	807	1,708	840	522	1,388	78
High Income							
Automatable	0.018	0.085	0.115*	0.148	0.018	0.107	0.0
Occupation	(0.023)	(0.094)	(0.060)	(0.093)	(0.059)	(0.140)	(0.0
N	15,486	1,028	1,719	845	422	399	1,1
				Labour Union Status			
Unionised							
Automatable	0.021	0.433	-0.139***	0.081	-0.341***	0.259***	0.842
Occupation	(0.045)	(0.302)	(0.049)	(0.096)	(0.075)	(0.077)	(0.2
N	6,816	308	473	452	27	346	15
Non-unionised							
Automatable	0.026	0.063	0.197***	0.194	-0.021	0.259*	-0.08
Occupation	(0.020)	(0.061)	(0.058)	(0.133)	(0.057)	(0.130)	(0.0
N	17,431	1,370	1,702	788	656	1,432	1,1

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Colu
sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as sh
and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed ef
derived from the SF-36 mental health responses in the HILDA survey.
*** p<0.01, ** p<0.05, * p<0.1

b) Disaggregated Effects of Working in an Automatable Occupation on Life Satisfaction by Income and Labour Union Status

Demographic Group	(1) Pooled	(2) Construction	(3) Manufacturing	(4) Transport	(5) Wholesale	(6) Retail	(7 Fina
	Dependant Variable = Life Satisfaction						
					Income Tercile		
Low Income	-0.003	-0.300	-0.010	0.101	0.547**	-0.162**	-0.1
Automatable	(0.033)	(0.185)	(0.115)	(0.068)	(0.259)	(0.060)	(0.1
Occupation	12,043	1,102	1,476	507	207	1,627	43
N							
Middle Income							
Automatable	0.015	-0.086	0.108**	0.124	-0.046	-0.234*	-0.10
Occupation	(0.023)	(0.196)	(0.040)	(0.089)	(0.070)	(0.125)	(0.0
N	15,775	807	2,367	840	522	1,388	78
High Income							
	0.002	-0.017	0.065	-0.084*	-0.048	0.027	-0.0

Automatable Occupation	(0.023)	(0.111)	(0.055)	(0.047)	(0.055)	(0.113)	(0.0
N	15,486	1,028	2,182	845	422	399	1,1
				Labour Union Status			
Unionised							
Automatable	0.018	0.146	0.018	-0.218	0.425	0.030	0.365
Occupation	(0.0351)	(0.190)	(0.0804)	(0.138)	(0.396)	(0.0796)	(0.1
N	6,816	308	545	452	27	346	15
Nonunionised							
Automatable	-0.005	-0.171	0.169**	0.147	0.026	-0.020	-0.0
Occupation	(0.0224)	(0.111)	(0.0732)	(0.122)	(0.0452)	(0.0913)	(0.04
N	17,431	1,370	2,277	788	656	1,432	1,1

Notes: Estimates of Eq. (2) are reported, with standard errors in parenthesis. The standard errors are clustered by occupation. Colu
sample, while columns (2)-(9) report the co-efficient by industry. Automatable occupations are defined by their level of RTI, as sh
and Dorn (2013) with the two-digit ANZSCO occupation classification code. Model controls for individual, time and area fixed ef
derived from the response to the question "How satisfied are you with your life?", with the response on an 11 -point Likert scale, f
*** p<0.01, ** p<0.05, * p<0.1