Minimum wage and the propensity to automate or offshore

Grace Lordan

London School of Economics

For the Low Pay Commission

5.11.2018

Acknowledgement

This report was prepared by Grace Lordan for, and was funded by, the Low Pay Commission (LPC). We are grateful for comments from the LPC and from discussants and participants at the LPC Research Workshops in April 2017 and 2018, and the LPC Research Symposium in September 2017.

Errors and omissions remain the responsibility of the authors alone.

Executive Summary

This report:

- Explores whether increases in the minimum wage change the employment probabilities of low-skilled workers who are reliant on automatable employment. This may happen if firms substitute their production process with technology following a minimum wage increase. For instance, job loss may arise if manufacturing firms substitute assembly line workers with robotic arms.
- Explores whether increases in the minimum wage change the employment probabilities of low-skilled workers who are reliant on jobs that could reasonably be offshored. Intuitive examples include firms out-sourcing their customer service teams to another country with lower minimum wages or outsourcing a component of their manufacturing process.
- Gives a full picture of any labour-market adjustment by industry and a variety of demographic groups to uncover differential responses. For example, we empirically assess whether older workers in automatable employment are worse off than younger workers in terms of employment probabilities after a minimum wage increase.

How we achieve our aims:

- The empirical analysis draws on the Quarterly Labour Force Survey data (QLFS) from 1994 – 2017. We distinguish between occupations that are high in automatable and offshorable tasks by drawing on UK data to re-create accepted definitions from the US. Each three-digit occupation is classified as either automatable or non-automatable, and offshorable or non-offshorable.

- We focus only on low-skilled workers. A person is classified as low skill if they are employed in an occupation that is paid a wage which falls in the bottom income quintile, and has a GCSE education equivalent or less.
- We calculate for each industry, area and year an automatable and offshorable employment share. This allows us to ask to what extent is the percentage of total automatable and offshorable employment affected by minimum wage increases. We further disaggregate the shares of employment analysis by industry, gender, ethnicity and age. For example, by doing this we can ask: to what extent is the percentage of total automatable employment held by males changed by minimum wage increases. This allows us to compare the vulnerability of males as compared with females and older workers with younger workers. We conduct regression analysis to relate these shares to the minimum wage, controlling for a number of other relevant factors. We allow for a period of adjustment by defining the minimum wage as its average over the current month plus the last 11 months.
- We also estimate regressions using individual-level data on low-skilled individuals, asking whether low-skilled individuals in automatable or offshorable work are more likely to lose their jobs in the next period as compared with those in non-automatable or non-offshorable work. This directly captures whether a person in automatable and offshorable work is more vulnerable to job loss following a minimum wage increase, as compared with similar persons in non-automatable or offshorable work. The individual analysis draws on the longitudinal labor force survey. These data follow people for 5 quarters, allowing us to consider the effects of minimum wage increases one year after the event.

- We complement these regressions with analyses that consider whether a person in an automatable job is more likely to stay in the same job following a minimum wage increase as compared with those in non-automatable work. This is important as staying in the same job between two periods has much lower levels of disruption for the individual.
- Firms may also substitute with technology and decrease the hours of certain employees, rather than cutting jobs. We consider this explicitly by relating the share of hours worked by low-skilled workers in either automatable or offshorable employment, in a particular industry, area, and year to the minimum wage. Using individual data we also assess the difference in reported usual hours worked between this year and last year by an individual one year following minimum wage increases.
- We replicate analysis using the Annual Survey of Hours and Earnings from 1998-2015 to consider the robustness of our findings to a second data source. Rather than focusing on low-skill individuals, these data allow us to focus on low wage individuals.

Our Findings:

- Minimum wage increases are followed by decreases in the shares of offshorable and automatable employment. On aggregate, these effects are modest. For example, a £1 increase in the minimum wage leads to a 0.24 and 0.15 percentage point decline in the share of automatable and offshorable employment respectively. For the shares of automatable employment analysis this amounts to an elasticity of -0.055 if evaluated at the current minimum wage of £7.50 for an increase to £8.50. The elasticity evaluated in the same way is -0.034 for the shares of offshorable employment analysis. Together, this implies that around 45,000 jobs are affected.

- Aggregate effects do mask larger changes in manufacturing, particularly for automation. For example, our estimates imply that a £1 increase in the minimum wage leads to a 0.58 and 0.34 percentage point decline in the share of automatable and offshorable employment in manufacturing respectively. The implied elasticities for a minimum wage raise from £7.50 to £8.50 are -0.13 and -0.086.
- Aggregate effects mask significant differences by demographic groups. Low-skilled males and older workers are affected the most, with larger effects also evident for Black low-skilled workers. For example, for older, low-skilled manufacturing workers in automatable employment there is an elasticity of -0.20 for a change in the minimum wage from £7.50 to £8.50
- Our analysis at the individual level implies that low-skilled workers in automatable or offshorable employment are less likely to keep their job and work fewer hours in the next period as compared with similar workers in non-automatable and non-offshorable jobs. For those working in manufacturing, males, and the oldest workers experience greater declines. For example, a 0.87 percentage point decline for low-skilled manufacturing workers in automatable employment older than forty for every £1 increase in the minimum wage (elasticity is -0.20 if evaluated for a minimum wage change from £7.50 to £8.50).
- Low-skilled workers in automatable or offshorable employment are more likely to switch jobs to either non-automatable or offshorable work in the next period following a minimum wage increase, as compared with those in non-

automatable or non-offshorable jobs. On aggregate, however, these effects are very modest.

- The analysis which considers how the shares of hours in automatable and offshorable employment respond to minimum wage increases also highlights significant but modest effects on aggregate, that are larger for males, older workers and Blacks.
- We note that the conclusions from our shares of automatable employment analysis are robust to a replication in ASHE, however for the shares of offshorable analysis replication we find coefficients that are centred around zero and never significant.

Looking Forward:

- We expect that the classification of offshorable jobs is likely to remain similar to that used in this report, however jobs classified as automatable are evolving.
- Drawing on a review of Google patents, supplemented with examples of robotics that are actively substituting for workers today there are three classifications of low-skilled jobs that are useful when framing the future.
- The first, are jobs that will never be fully automatable, given that they require human interaction in an unpredictable sequence of actions as well as empathy from the provider. These jobs include childcare and hairdressing.
- The second are jobs where human interaction may not be part of the value of service to customers on some occasions, and there is a definite sequence of actions that can be codified. Examples include waiting staff and bartenders. We expect continued automation of these jobs, with a polarization by quality where some jobs are provided by humans and others by robots.

- The third are jobs where customers care less about whether or not the work is carried out by a human, and innovation for robotic substitutes has made good progress. Examples include delivery driver or security guard. This is the group of jobs which is the most at risk of disappearing.
- Jobs lost to automation will be met with the creation of new jobs that require a different set of skills. We do not know if these will be in equal number to those lost. Just because all jobs lost have been replaced with new jobs in the past does not mean that this will continue to occur in the future. Replacement at these levels will become less likely as machines continue to learn. So, there is a role for policy in the ongoing monitoring of trends, and to consider how the rents earned by machines should be re-distributed within society as technology adoption accelerates.

Introduction:

At the time of publication, the National Living Wage (NLW) is £7.83, having increased in 1 April 2018 from £7.50 and is set to rise to 60 per cent of median hourly earnings, around £8.60, by 2020 in the UK. In a landscape of economic uncertainty – including an advancing global economy and increasing investment in the research and development (R&D) of robots – it is prudent to think about how minimum wage increases affect the low-skilled workers most vulnerable to these changes. This report considers the effect of minimum wages on automatable and offshorable employment – jobs in which employers may find it easy to substitute robots or offshore the tasks done by domestic workers – focusing on low-skilled workers from whom such substitution may be intuitively accelerated by minimum wage increases.

Overall there are no shortage of papers that consider the effects of the minimum wage in the UK. In general, these studies have focused on the potential changes to employment opportunities for the low skilled, and the majority suggest that overall employment effects are minimal (see Hafner et al 2016, Megan de Linde Leonard et al 2014), and for specific sub groups in society[1,2]. However, there is also evidence that other sub groups do lose out on employment opportunities when the minimum wage increases. Specifically, these groups are part-time females (Dickens et al, 2015; Bewley and Wilkinson 2015), part-time workers in general (Hafner et al, 2016), service industry employees (Fidrmuc and Tena, 2013) and care home workers (Machin and Wilson, 2004). Notably, the paper by Dickens et al (2015) finds that effects on part-time females are exacerbated during recessions suggesting that firms may resort to culling jobs when minimum wage increases can no longer be absorbed

[1] For example, Stewart (2004) who explores employment effects for adult and youth, men and women.
[2] For example, Dickens et al (2015) who explore employment effects for workers aged 22-24 years.

in prices. In addition, Papps and Gregg (2014) highlight that overall employment effects are limited, but this masks a significant amount of job switching for low-paid workers after minimum wage increases, which is not without costs to the employee or the firm.

Overall, the studies cited here do vary in methodological approach so comparisons are difficult, however it is clear that exploring for heterogeneity of effects within sub groups maybe important so that the winners and losers of minimum wage increases can be properly considered. While minimum wage proponents may argue that aggregate effects of the minimum wage are all that matters, an employment maximisation goal can also be augmented to protect certain more vulnerable groups in society should policy makers wish to do so. This protection may come in the form of re-training or a guaranteed basic income plan if re-employment is unlikely[3].

Employment effects aside, and bearing in mind the importance of exploring heterogeneity in minimum wage effects, Lordan and Neumark (2017) have recently emphasised that employers can respond in a number of other ways to increases in the minimum wage. For example, they may alter job amenities (Simon and Kaestner, 2004) or compress wages (DiNardo, Fortin and Lemieux, 1996 and Autor, Manning and Smith, 2010). Lordan and Neumark (2017) also emphasise that minimum wages may act as a price shock to the marginal cost of labour, which if high enough, can cause firms to substitute labour with relatively cheaper technological innovations. The overall end being that minimum wage increases have the potential to change the type

[3] These kinds of trade-offs are akin to trade-offs commonly made when making decisions about how resources will be devoted to health in the UK. The quality adjusted life year (QALY) is the primary unit of effectiveness used to inform the decisions made by National Institute for Health and Care Excellence, and explicitly weights in favor of younger individuals. This contrasts with countries who make decisions based on the Disability Adjusted Life Year which weights in favor of working age populations when allocating health resources. In addition, there is now an emergence of a super QALY, which allows the incorporation of subjective considerations. So, the idea of maximizing health subject to some groups in society being more protected than others is part of the regular discourse.

of work available for low-skilled individuals. That is, if the partial elasticity of substitution between automatable workers and technology is relatively large and positive, a firm can maintain an identical level of production by reducing their number of automatable workers and increasing their investments in technology. This becomes more appealing as the wage rate of automatable workers increases. Thus, in this case if a particular individual is only a good match for automatable low-skilled work they are likely to be losers in this scenario, as they will not find alternate work. This is most likely for groups of workers who find it hard to re-train.

In previous work, Lordan and Neumark (2017) explored whether the minimum wage affects the employment possibilities for workers relying on automatable employment indirectly by considering if individuals in automatable jobs are likely to lose jobs, following minimum wage increases in the US. For example, job loss may arise if manufacturing firms substitute assembly line workers with robotic arms. However, we note that the adoption of new technology itself may also create jobs within firms as they require workers to maintain their new technologies. These roles are likely to be of higher skill than the ones the technology replaced, with the result being a pattern of labour reallocation away from low-skilled automatable jobs if minimum wage increases raise the marginal cost of labour to a level where firms perceive it is cheaper to substitute towards technology. Given the current attention being paid to the potential for robots to cause unrecoverable job loss in the academic literature (for example Michaels and Graetz, 2015; Michaels and Graetz, 2017), the first objective of this work is to replicate the analysis in Lordan and Neumark (2017) for the UK. To our knowledge this is the first exploration of this kind for the UK context.

It is also possible that firms substitute their production process with cheaper labour from a different geographic location. Intuitive examples include firms out-sourcing their customer service teams to another country with lower minimum wages or outsourcing components of their production process. This implies that a firm may consider offshoring some of its activities if wage bills get too high. Again, this change may cause firms to hire workers who perform entirely new tasks that complement these changes to the production process. For example, the offshoring firm may hire individuals to co-ordinate their offshoring activities. In this case, low-skilled workers in the UK who are in jobs that are offshorable are the most vulnerable to minimum wage increases. The second aim of this work is therefore to explore whether there were changes to the employment opportunities of low-skilled workers employed in offshorable jobs following a minimum wage increase.

Together this work aims to provide a deeper understanding on how minimum wage policies have been shaping the type of employment available within the UK for low-skilled workers (defined as those of low education working in the lowest-paid occupations) within industries and for particular demographic groups. In particular, we will emphasise effects for low-skilled workers who are reliant on automatable or offshorable jobs. Specifically, we will empirically assess whether, following a minimum wage increase, there are declines in:

i) the share of employment that is automatable and offshorable;

ii) the propensity to lose employment in an automatable and offshorable job;

iii) the propensity to switch from an automatable or offshorable job, to a non-automatable or non-offshorable job;

iv) the share of hours that are automatable and offshorable; and

v) the number of hours worked.

We choose to focus on automation and offshorability as they have been the two dominant forces that have threatened jobs in the UK in the last decades. This arises, because as substitutes for specific types of labour inputs, automation and offshorability offer the potential for a cheaper production process if the unit price of labour gets too high. Given that minimum wage policies make a firm's production process more expensive, by directly raising the marginal cost of labour, the potential for substitution of labour in the production process is likely to become more appealing.

This work contributes to the UK minimum wage literature in a number of ways. First, we are the first to consider how the availability of offshorable and automatable jobs in the UK has changed following minimum wage increases in past years for low-skilled workers. We note that the analysis of the share of offshorable employment is unique to the literature. However, the analysis of the share of automatable employment is a replication of the analysis conducted by Lordan and Neumark (2017) for the US. In their work, the authors highlighted that women and older workers (>=40 years old) were the most affected, in terms of job loss, following minimum wage increases, with the effects mainly falling on the manufacturing industry. They highlight that workers reliant on automatable employment aged between 26 and 39 years were the most susceptible to job switching – a cost often not highlighted in the minimum wage literature. Lordan and Neumark (2017) emphasised that their main contributions were to highlight that low-skilled workers in automatable work were vulnerable following a minimum wage increase, and that the groups most affected by automation in the past have been understudied in the minimum wage literature. A related analysis – Aaronson and Phelan (2017) – analyzed the susceptibility of low-wage employment to technological substitution. Their study provides some evidence that firms may automate routine jobs in response to a minimum wage increase, reducing employment opportunities for workers in routine jobs.

Second, we give a full picture of labour-market adjustments by industries and a variety of demographic groups. This allows us to uncover differential responses. Together, our analyses provide evidence on how employment composition has changed following minimum wage increases in the UK through to 2017, as well as covering many issues that are often ignored in the minimum wage literature, such as the effects on older less-skilled workers.

Third, we investigate whether employment shares of offshorable and automatable work shift in response to minimum wage increases with a lag. This is important as it may take firms a period of time to react and substitute labour as a factor of production if the production process is hard to change (Sorkin, 2015).

Overall this work is timely given the Government has committed in the UK to regularly revise its minimum wage upwards in line with the median earned wage. Therefore, our analysis has a clear and general policy perspective given that it informs us of the likelihood of losing low-skilled automatable and offshorable employment shares following minimum wage hikes, as well as highlighting who is the most vulnerable in terms of any labour reallocations.

The empirical analysis draws on Quarterly Labour Force Survey data (QLFS) from 1994 – 2017. We distinguish between occupations that are high in automatable and offshorable tasks by drawing on UK data to re-create the accepted US definitions provided in Autor, Dorn and Hanson (2015), Firpo, Fortin, and Lemieux (2011) and Autor and Dorn (2013). We note that for the data that we draw on around a third (32%) and nearly half (47%) of the individuals denoted as being in automatable and offshorable work respectively are working in manufacturing, so intuitively the conclusions drawn in the pooled analysis are driven predominately by this industry. Overall, we consistently highlight that minimum wage increases decrease the shares of offshorable and automatable employment following a minimum wage increase. On aggregate, these effects are very modest. For example, a £1 increase in the minimum wage leads to a 0.24 percentage point decline in the share of automatable employment. This amounts to an aggregate elasticity of -0.055 if evaluated at the previous minimum wage of £7.50 with 1/3 of the current jobs available being classified as automatable[4]. The elasticity evaluated in the same way is -0.034 for the shares of offshorable employment analysis (a coefficient that implies a 0.15 percentage point decline for a £1 increase in the minimum wage). Note interpreting elasticities in this way implies no changes to the classification of automatable or offshorable jobs[5].

We note the aggregate effects mask larger changes in manufacturing, particularly with respect to automation. That is, our estimates imply that a £1 increase in the minimum wage leads to a 0.58 and 0.34 percentage point decline in the share of automatable and offshorable employment in manufacturing respectively. Here the implied elasticities for a raise from £7.50 to £8.50 are -0.13 and -0.086.

We note that the pooled analysis does mask significant heterogeneity by demographic groups. That is, males and the oldest workers are affected the most, with larger effects also evident for Black, low-skilled workers.

---

[4] Elasticity at any wage rate can be calculated as (coefficient on minimum wage/proportion of automatable jobs)/(level increase/chosen minimum wage rate).

[5] If the value of the elasticity is >0 and <-1 the elasticity is inelastic. The closer the elasticity is to 0 the more limited the response, but this changes as the minimum wage gets larger. As the elasticity approaches 1 the shares of employment are becoming more sensitive to minimum wage changes.

Finally, we note that the conclusions from our shares of automatable employment analysis are robust to a replication in ASHE, however for the shares of offshorable analysis replication we find coefficients that are centred around zero and never significant.

Similar conclusions to our shares of employment analysis emerge in additional analysis, which considers the likelihood that a low-skilled worker in automatable or offshorable employment remains employed in the next period as compared with a low-skilled worker in non-automatable or non-offshorable employment following a minimum wage increase. Overall, low-skilled workers in automatable or offshorable employment are less likely to keep their job and work fewer hours in the next period, however these differences are modest overall. In addition, the effects for automation are always larger. We also note that for those working in manufacturing, males and the oldest workers experience greater declines (for example, a 0.87 percentage point decline for low-skilled manufacturing workers in automatable employment older than forty for every £1 increase in the minimum wage, which gives an implied elasticity of -0.20 if evaluated for a change from £7.50 to £8.50). We find some consistent evidence that low-skilled workers in automatable or offshorable employment are more likely to switch jobs to either non-automatable or offshorable work in the next period following a minimum wage increase.

Together, our work suggests that firms in the UK may re-assess their production processes following a minimum wage increase, and consider offshoring and automation as their labour costs get higher. Given the data available, we note that we cannot comment on anticipatory effects which may also be significant. Our analysis also points to older workers as more vulnerable to these changes – and arguably the group who will find it the hardest to re-train to allow them to take on new roles. The latter is also consistent with our job-switcher analysis which suggests that older workers are less likely than middle age workers to switch jobs following a minimum wage increase.

A limitation of our analysis is that it is retrospective and our findings are driven by a couple of decades of change in the manufacturing industry, which are arguably near to complete. That is, the jobs that will be offshorable and/or automatable in the future may be very different to what we have seen in the past. We finish the paper by discussing whether the classifications of automatable and offshorable jobs are likely to remain similar to that used in this report. We conclude that while automatable jobs continue to evolve, there is limited scope for further extensions to offshorable jobs.

Drawing on a review of Google patents, supplemented with examples of robotics that are actively substituting for workers today, we provide commentary on ten popular low-skilled jobs. Notably, these ten jobs are currently classified as non-automatable. This review suggests that there are roughly three types of jobs among those considered. The first, are jobs that will never be fully automatable, given that they require human interaction in an unpredictable sequence of actions as well as empathy from the provider. These jobs include childcare and hairdressing. The second are jobs where human interaction may not be part of the value of service to customers on at least some occasions, and there is a definite sequence of actions that can be codified. There have also already been inroads into the creation of technology to substitute for these workers. Examples here include waiting staff and bartenders. We envisage continued automation here, with an ultimate polarization by quality where some jobs are provided by humans and others by robots. Finally, are the jobs where customers may care less about whether or not the work is carried out by a robot or a human, and innovation for robot substitutes has been making good progress. Examples include delivery driver or security guard. We envisage that this is the group of jobs which is the most at risk of disappearing completely.

We acknowledge that further job types lost to automation will be met with the creation of new jobs, most obviously to complement and run the new technology. However, it seems unclear whether these new jobs will be the same in number and will require an entirely different set of skills, even if in the past jobs that have been replaced by technology have always been replaced. The evidence in this report suggests modest endogenous technology adoption as the minimum wage increases, therefore policy makers may want to monitor these trends going forward with a view to considering what skills low-skilled individuals may need to be employed should these effects amplify in the future.

Methodology

Low-Skilled Individuals

Our analysis focuses on low-skilled individuals who are employees. We acknowledge, that this is a partial analysis in the sense that we do not quantify whether jobs lost to low-skilled workers are gained by others further along the skill distribution. This is because we are primarily interested in low-skilled workers. This is also in line with the majority of studies on employment effects, which do not comment on whether negligible employment effects are offset by lower wages for higher-skilled individuals.

We also envisage a labour market that is entirely separable by skill. That is to say low-skilled individuals cannot – at least without more training, which takes time – obtain a high-skill job. Therefore, this analysis may be viewed as focusing on how minimum wage increases may cause changes to the type of work available for and done by low-skilled workers only.

Throughout the analysis we consistently define low-skilled individuals as those who are working in the lowest-paid occupations in the UK, while also having low levels of education. We focus only on those born in the UK to circumvent the fact that immigration flows may cause the composition of this group to fluctuate over time. A documentation of the shares of employment analysis which includes immigrants is included in Appendix D, and we note here that this decision does not affect the estimates. Practically, we calculate earnings for each occupation in each year, and based on this distribution only include in the analysis those in the bottom quintile (mean minimum weekly gross wage is 153 GBP in 2015 prices) with a GCSE equivalent or less.

Measuring Automatable Employment

To create our measure of automatable employment we draw on the UK Skills and Employment Surveys series data covering the years – 1986, 1992, 1997, 2001, 2006 and 2012 (Felstead et al, 2014)[6] – and, given the data available, create a measure of routine task intensity that is as close to the US version created by Autor and Dorn (2013) and Autor et al. (2015) as possible. In particular, routine task intensity in each three-digit occupation is defined as:

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

where T_k^R, T_k^M, and T_k^A are the levels of routine, manual, and abstract task inputs for occupation k measured at the 3-digit level.[7] Thus, Equation (1) is increasing in the absolute and relative quantity of tasks that are automatable within occupation k.

[6] These data contain responses from more than 25,000 incumbents and covers their thoughts on their job context and activities.
[7] These levels are defined using variables from versions of the Dictionary of Occupation Titles, where incumbents are asked to grade the level of their occupation with respect to particular attributes.

We expect routine tasks to involve a repeated sequence of actions, to be easily codifiable, and therefore substitutable with technology. For our purposes this is measured as the response to the question 'How often does your work involve short repetitive tasks'. The response options are 'never', 'rarely', 'sometimes', 'often' or 'always'.

Manual tasks require actions that are not generally predictable in sequence, so substitution with technology is limited. They have a lot of variability and are therefore limited in their predictability. This lack of predictability ensures they are hard to code, so opportunities to substitute with technology are more limited. In order to capture how this relates to individual occupations we utilise responses to the question 'how much variety is there in your job?'. This question has response options of 'a great deal', 'quite a lot', 'some', or 'none at all.'

Abstract tasks require high-level thinking that is more complementary with technology (Autor et al, 2013). This is captured by 'would you say the importance of analyzing complex problems in depth is 'essential', 'very important', 'fairly important', 'not very important', or 'not at all important'?'. Specifically, Equation 1 is calculated for three-digit UK Standard Occupation Codes (SOC) 2000 occupation codes, based on standardized responses to these questions (mean 0 and standard deviation of 1) and matched to Quarterly Labour Force Survey data from 1992 to 2016[8]. We note that 32% of the individuals denoted as being in automatable work are in manufacturing. That compares with just 9% in hotels and restaurants.

[8] The coding system in the UK changed twice between 1992-2017. Between Q2 1992- Q1 2002 the QLFS used UK SOC 90. We utilize a cross walk described in Lordan and Pischke (2016) to assign each UK SOC 90 code to a UK SOC 2000 value. In 2010 there was another minor coding change. The authors have created a cross walk to assign a UK SOC 2000 code to each UK SOC 2010 code in the QLFS.

Our analysis also considers the US version created by Autor and Dorn (2013) and Autor et al. (2015) as a robustness check.

Measuring Offshorable Employment

Following Firpo, Fortin, and Lemieux (2011) and Autor and Dorn (2013) we wish to create an index that represents how offshorable any occupation *j* is. This is given by:

$$OF_j = -\frac{\sum_{1}^{M} P_j}{M} \quad (2)$$

We again base this on UK Skills and Employment Surveys series data. Specifically, M represents a number of proxies P that relate to offshorability, which capture the degree to which an occupation does not require physical proximity to a specific geographic location. We aim to copy the intuition underlying the US proxies which capture the level to which an occupation requires: 'face-to-face discussions'; 'establishing and maintaining interpersonal relationships'; 'assisting and caring for others'; 'performing for or working directly with the public; 'coaching and developing others'; 'inspecting equipment, structures, or material'; 'handling and moving objects'; 'operating vehicles, mechanized devices, or equipment'; 'repairing and maintaining mechanical equipment'; and 'repairing and maintaining electronic equipment.'

For the version based on the UK data the items capture the level to which the occupation requires: 'teaching people'; 'counselling advising or caring for customers or clients'; 'dealing with people'; 'knowledge of use or operation of tools'; and 'using the internet'. Response options for all of these questions: are 'essential'; 'very important'; 'fairly important'; 'not very important'; or 'not at all important.' We standardize responses to have a mean of 0 and standard deviation of 1. We multiply 'using the internet' by -1 so it is increasing in an occupation's level of offshorability. Similarly, for both the UK and US versions we multiply the index by -1. We note that 47% of the individuals denoted as being in offshorable work are in manufacturing. The US version, provided by Firpo, Fortin, and Lemieux (2011) is considered as a robustness check[9] in our analysis.

Automatable and Offshorable Jobs

Table 1 provides examples of occupations that are automatable and offshorable, as well as occupations that are non-automatable or non-offshorable based on the UK data. We note that the correlation across these jobs is 0.25. Overall, the jobs that are labelled as automatable are easily substitutable with robotics (for example, assemblers and routine operatives) or computer software (for example, administrative occupations in filing records). That is, the technology is readily available. In contrast, the jobs that are labelled as non-automatable are much less predictable in terms of their sequence of actions (for example, transport drivers and operatives) and often require contact with clients (for example, personal service occupations).

Notably, the jobs that are offshorable are mainly found in manufacturing. This is consistent with the US categorisations provided by Firpo, Fortin, and Lemieux (2011). Examples include food preparation trades, and textile and garments trades. Intuitively, these products can be imported rather than produced at home, with arguably limited effects on the consumer. Conversely, a job is non-offshorable if it requires a specific geographical location of the worker to get their tasks done. For

[9] These were matched using the same method detailed in footnote 8.

example, builders need to work in specific locations to construct buildings, and a child carer needs to be in a specific location to watch over a child.

Shares of Automatable Employment Analysis:

Based on Equation (1) for each industry *i*, within each area *a* (defined as the official government office regions), in year *t*, we calculate an automatable employment share as follows:

$$RSH_{iat} = (\sum_{k=1}^{K}(L_{iat}) \cdot 1[RTI_k > RTI^{P66}])(\sum_{k=1}^{K}(L_{iat}))^{-1} \quad , \tag{3}$$

In Equation (3), L_{iat} is equal to total employment in industry *i* in area *a* at time *t*. $1[.]$ is an indicator function taking the value of one if an occupation is in the top third of the employment-weighted distribution of *RTI* (routine task intensity) across occupations, using only low-skilled workers. The numerator is then the share of automatable low-skill employment in a particular industry, area, and year, and the denominator is total low-skilled employment in that industry, location, and year. The data we draw on is the Quarterly Labour Force Survey:

Our analysis initially focuses on the following specification:

$$RSH_{iat} = b_1 MW_t + A_a \gamma + A_t \lambda + I_i \varphi + X_{iat} + \varepsilon_{iat} \quad , \tag{4}$$

where MW_t denotes the minimum wage at time *t* adjusted to 2015 prices (see data section for how the minimum wage is defined specifically). Equation (4) includes area (A_a) and industry (I_i) fixed effects. It also includes area specific time trends[10] (A_t). X_{iat} is a set of control variables, which may simultaneously predict the dependent variable, while being correlated with the minimum wage over time[11]. Negative and significant

[10] We note that in a robustness analysis we swap area-specific time trends for industry-specific time trends to allow for the fact that technology may diffuse differently across industries. This change does not affect the estimates significantly.
[11] These are: 1) Area level unemployment rate. This is calculated using the Quarterly Labour Force

estimates of b_1 would imply that the share of employment that is automatable declines in response to minimum wage increases.

We next turn to disaggregating these effects across industries and demographic groups, to see whether there are industries or groups particularly vulnerable to automation caused by minimum wage increases. We focus on differences in effects by age and sex, and we also examine differences by ethnicity. Specifically, for ethnicity we look at Whites, Blacks and Asian workers (here Asian is defined as someone who identifies with their ethnic origin as being Indian, Pakistani or Bangladeshi. We do not look at other ethnicities given small cell sizes). For age, consistent with Lordan and Neumark (2017), we look at aged 40 and over, those aged 25 or younger, and the intermediate group aged 26-39.

To unpack the impact of minimum wage increases by age, gender, and race, we use measures of task intensity for each subgroup (indexed by c), as follows:

$$RSH_{ciat} = (\sum_{k=1}^{K}(L_{ciat})\cdot 1[RTI_k > RTI^{P66}])(\sum_{k=1}^{K}(L_{ciat}))^{-1} \quad . \tag{5}$$

In this case the numerator is the share of automatable employment held by a particular sub-group in a specific industry, area, and year, and the denominator is total employment of a particular subgroup by industry, area, and year. We estimate Equation (4) for the separate subgroups, indexed by c, using RSH as defined in Equation (5).

Survey. We note that taking the employment rate instead of the unemployment rate as a control variable does not affect the point estimates. 2) Industry level unemployment rate. This is calculated using the Quarterly Labour Force Survey. 3) Area level demographics that vary over time: average age, education, gender. 4) Occupation demographics measured at the area/industry/year level: average age, education, gender.

Shares of Offshorable Employment Analysis:

Based on Equation 2, for each industry *i*, within each area *a* (defined as the official government office regions), in year *t*, an offshorable employment share as follows:

$$OES_{iat} = (\sum_{k=1}^{K}(L_{iat}) \cdot 1[OES_k > OES^{P66}])(\sum_{k=1}^{K}(L_{iat}))^{-1} \quad , \tag{6}$$

Replacing RSH with OES in Equation 4, allows us to empirically assess if the share of employment that is offshorable is declining in response to minimum wage increases. In a similar vein, we replace RSH with OES in Equation 5 and consider subgroup analyses. This allows us to get the full picture of labour-market adjustments by industry and demographic groups. That is, we can point to the groups most at risk of offshorable employment share shifts in response to the minimum wage.

For the shares of employment analysis we will also often report implied elasticities given the coefficient on the minimum wage. These are evaluated based on an increase from £7.50 (the previous level for those aged 25 and over) to £8.50 and also assume one third of the jobs are automatable (given the construction of the measure of automatability). These interpretations rely strictly on the definitions of automation as given and are lower bounds if more jobs are now automatable. This is subsequently discussed further.

Data

Our main data source for the shares of employment analysis is the QLFS[12]. These data are matched to monthly age-specific data on the minimum wage that was

[12] Office for National Statistics. Social Survey Division, Northern Ireland Statistics and Research Agency. Central Survey Unit. (2018). *Labour Force Survey Household Datasets, 2002-2017: Secure Access*. [data collection]. *3rd Edition.* UK Data Service. SN: 7674, http://doi.org/10.5255/UKDA-SN-7674-3

gathered by the author. Consistent with Lordan and Neumark (2017) we allow for a period of adjustment by defining the minimum wage as its average over the current month plus the last 11 months[13]. The minimum wage is measured in 2015 prices. We do not produce sub-analysis for agriculture, forestry and fishing and energy and water as the sample sizes are too small to calculate RSH_{iat} by area and year. We create our share of employment variable on a yearly basis, and similarly construct an annual average of the minimum wage variables by calculating its average by industry, area and year.

Individual-Level Analysis for Automatable Employment:

We also estimate regressions using individual-level data on low-skilled individuals. Specifically, we estimate the model:

$$Emp_{jiai+1}=b_1(RSH_{jiat}\cdot MW_{at})+ b_2RSH_{jiat} +T_t\cdot S_s\lambda + I_i\varphi + \varepsilon_{jiat} \quad , \tag{7}$$

where *Emp* is the probability that the j^{th} person is employed in industry *i*, area *a*, at time *t*+1. It is assigned zero if a person was unemployed in *t*+1. The sample consists of those employed in period *t*, and either employed or unemployed (i.e., in the labour force) in period *t*+1. As discussed in Lordan and Neumark (2017) we can more reliably interpret these transitions, for this sample, as reflecting job loss due to minimum wage increases. That is, by starting with those who are employed and looking at the effects on unemployment in period 2, we can have certainty that the effects we identify are informative regarding individuals losing their jobs, rather than

[13] Appendix E documents a robustness check which defines minimum wage in the shares of employment analysis as the contemporary minimum wage (see Table E.1) and minimum wage with a lag (see Table E.2). We note that the lagged results are stronger and more amplified than those that consider the contemporary measure. We tentatively note that this points to a period of adjustment. We also note that we have estimated models that add to these specifications, the one-year forward minimum wage. This is never significant but the estimates are noisy and negative so we cannot fully rule out anticipatory effects.

being driven by individuals transitioning into retirement or caring voluntarily with no intention of return.

Equation (7) relates job loss to workers having held a routine job (defined based on the respondent's own occupation code) in period *t*, and facing a minimum wage increase. The coefficient on the interaction $RSH_{jiat} \cdot MW_{at}$ – b_1 – is informative as to whether a person in automatable work is more vulnerable to job loss following a minimum wage increase, as compared with those in less automatable work. The minimum wage is defined as the level at time *t* in 2015 prices. We can only look at those initially employed because we need to classify the routine task intensity of jobs, so we are capturing only flows out of employment and into unemployment[14].

Note that Equation (7) includes a full set of area-by-year interactions[15], to allow for differential time patterns across areas. Thus, this is a much more conservative analysis, as compared with Equation 4 where we had to rely on area-specific time trends only. Given the inclusion of the area-by-year interactions, the main minimum wage effect drops out, and identification of the coefficient on the interaction comes from variation in the availability of automatable jobs within government regions across time.

All other definitions are consistent with Equations (1) through (4). Under the expectation that individuals working in automatable jobs at the time of a minimum wage increase are more likely to have lost jobs by the next period as compared with

[14] We note that this means that this analysis only captures retention for those who are currently in automatable or offshorable work. Given our focus is on how this group of workers are affected following minimum wage increases this makes sense, however any significant negative effects may also be explained by those who are searching for employment taking up low-skilled automatable or offshorable jobs which put those currently employed out of work, while the same search group do not take up non-automatable or non-offshorable jobs. This seems unlikely.

[15] In a robustness analysis we swap the area-by-year interactions for industry-by-year interactions and the estimates do not change. We note that the minimum wage effect that is identified in this specification is negative, centred around zero and never significant.

individuals that are in jobs that are not automatable, we expect the coefficient on b_1 to be negative and significant. We unpack heterogeneity in b_1 by estimating Equation (7) separately by industry and demographic subgroup.

We complement these regressions with analyses that consider a dependent variable that equals one if an individual had the same occupation code in the interview year, and zero otherwise (including both the unemployed and job switchers, but excluding those who leave the labour force). In these analyses, a negative and significant b_1 captures movements of labour out of employment in automatable tasks following a minimum wage increase (either to other work in non-automatable tasks or dis-employment).

Individual-Level Analysis for Offshorable Employment:

Replacing RSH with OES in Equation 7, allows us to consider identical analysis for offshorable employment. That is, we ask whether someone who is in offshorable employment in period *t* is less likely to be 1) still employed and 2) employed in the same job in period *t+1* as compared with those who hold occupations that are less offshorable in period *t.*

Individual Level Analysis Data

Our individual level analysis relies on the Longitudinal Labour Force Survey (LLFS). We calculate the probability of still being employed with a one-year gap. The minimum wage for the individual-level analysis is defined, in 2015 prices, at the level that was in effect when the person was first interviewed for the LLFS.

Analysis of Hours:

Our analysis so far has focused on employment effects. However, there is also a potential for hours to decrease in automatable or offshorable employment following a minimum wage increase. We consider hours explicitly by re-estimating Equation (4) and relating minimum wage variation to the share of automatable or offshorable hours. Here, the numerator is the number of hours worked by low-skilled workers in automatable (offshorable) employment in a particular industry, area and year. The denominator is the total hours worked in an area in a given year.

We also re-estimate Equation (7) with the difference in reported usual hours worked between this year and last year by an individual as the dependent variable (this analysis uses the LLFS instead of the QLFS). Specifically, we focus on those who are in employment in the two periods, and reported positive hours worked at both time points.

Results:

Effects on Employment Shares

The results for the employment shares analysis (Equation (4)) are reported in Table 2. From the top panel of Table 2 Column (1), the pooled analysis suggests that a £1 increase in the minimum wage leads to a modest 0.24 percentage point decrease in the share of automatable jobs done by low-skilled workers. This amounts to an aggregate elasticity of -0.055 if evaluated at the current minimum wage of £7.50 with 1/3 of the current jobs available being classified as automatable[16]. This assumes no changes to the classification of automatable jobs.

[16] Elasticity at any wage rate can be calculated as (coefficient on minimum wage/proportion of automatable jobs)/(level increase/chosen minimum wage rate).

However, the sub-analysis by industry suggests that the true effects for all industries, with the exception of manufacturing, are not statistically significant from zero. In manufacturing, the effects are more substantive, suggesting that a minimum wage increase of £1 causes a 0.58 percentage point decrease in the share of automatable jobs done by low-skilled workers in manufacturing. Here the implied elasticity is -0.131 and is also notably more substantial.

The bottom panel of Table 2 documents the results for the share of offshorable employment analysis. Column (1) suggests that a £1 increase in the minimum wage leads to a very modest 0.15 percentage point decrease in the share of offshorable jobs done by low-skilled workers (elasticity = -0.034). However, these effects are again driven by more substantive effects in manufacturing. We note that you cannot add the effects across the automation and offshorable models as the correlation between the automation and offshorable indicators is 0.25. The coefficients for all other industries in the sub-analysis are centred around zero and not significant. Specifically for manufacturing, the estimates imply that a £1 increase in the minimum wage leads to a 0.34 percentage point decrease in the share of offshorable jobs available for low-skill workers in manufacturing (an elasticity of -0.077).

Table A.1 in Appendix A documents the same analysis, with the proxy of automatable and offshorable work changed to the US definitions. We note that the overall conclusions are similar. That is, there are significant but still modest negative effects on the overall shares of automatable and offshorable work, which are driven mainly by relatively large effects in manufacturing. However, the estimates are amplified by about 50% in comparison to those documented in Table 2.

Table 3 disaggregates the analysis by gender. From Table 3, minimum wage changes predict more movement in the shares of employment for males as compared with females. Specifically, on aggregate, the estimates imply that a £1 increase in the minimum wage reduces the shares in automatable and offshorable work for males by 0.32 and 0.23 percentage points respectively (implied elasticities being -0.072 and -0.052). In contrast, the same figures for females are never significantly different from zero. Notably, the effects for manufacturing are more substantive. For example, the share of automatable employment for males decreases by 0.84 percentage points in response to a £1 increase in the minimum wage (an elasticity of -0.20). In comparison, for females, this fall is more modest at 0.32 percentage points (an elasticity of -0.072). Table 3 also documents significant declines for the male share of automatable employment in banking and finance, as well as for the male offshorable share in manufacturing[17].

In Table 4, we document the results disaggregated by age. From Column (1), the shares of automatable jobs for low-skilled older workers (≥ 40 years old) and middle aged workers (>25 years and <40 years) are the most affected. For example, for workers who are 40 years or older there is a 0.60 percentage point decrease in their share of automatable employment following a £1 increase in the minimum wage (an elasticity of -0.14). The same figure for workers between the ages of 26 and 39 is 0.39 percentage points (an elasticity of -0.089). The effects for workers who are 25 years or younger are not significantly different from zero.

The effects are largest for manufacturing for the oldest workers. That is, a £1 minimum wage increase decreases the shares of automatable employment for workers aged 40 and over by 1.05 percentage points. This implies an elasticity of -0.24 for a minimum wage increase from £7.50 to £8.50. For workers aged between 26 and 39

[17] We note that the same pattern emerges if we consider the US proxy for offshorable and automatable work, however consistent with the pooled analysis the effects are significantly amplified (see Table A.2 in Appendix A).

the effect is also significant and relatively substantive (with an implied decrease of 0.62 percentage points, or an elasticity of -0.14). For workers aged between 26 and 39 the sub-analysis for business and finance also implies negative and significant effects (with an implied decrease of 0.38 percentage points for every £1 increase in the minimum wage, an elasticity of -0.09).

Turning to the analysis of the shares of employment for offshorable jobs, the estimates suggest that older workers (>=40 years) are the only group significantly affected in aggregate by minimum wage increases. Specifically, a £1 minimum wage increase implies a 0.26 percentage point decline in the share of offshorable employment available for these workers overall (an elasticity of -0.059). However, both the oldest (40 years or older) and middle aged (between 26 and 40 years) have significant effects in the manufacturing sub-analysis. Specifically, a £1 minimum wage increase decreases the shares of offshorable employment for the oldest workers by 0.61 percentage points (an elasticity of -0.138). For workers aged between 26 and 40 years this is 0.36 percentage points (an elasticity of -0.082).[18]

Table 5 disaggregates the estimates from Table 2 by race. For Whites, the significant pooled estimates are largely driven by changes to the shares of low-skilled jobs that are both automatable and offshorable in manufacturing. For instance, a £1 minimum wage increase implies a 0.45 percentage point decline in the share of offshorable employment available for low-skilled White workers in manufacturing (an elasticity of -0.102). The figure for White workers in automatable jobs in this industry is 0.71 percentage points (an elasticity of -0.161). The effects for Blacks in the share of automatable employment analysis are larger. For example, the pooled

[18] This narrative is robust to considering the US proxies for automatable and offshorable work. See Table A.3 in Appendix A.

analysis implies that a £1 increase in the minimum wage leads to a 0.60 percentage point decline in their share of automatable employment (an elasticity of -0.136). This is driven by substantive declines in manufacturing in response to minimum wage hikes – specifically 1.06 percentage points for a £1 increase (an elasticity of -0.241). The effects for Blacks in the share of offshorable employment analysis are not significant. For Asians, both the pooled and sub-analysis for manufacturing yield insignificant minimum wage effects on both the share of automatable and offshorable employment respectively, which are also centred around zero. Notably, the only shares to be significantly affected pertain to banking and finance. Specifically, the estimates in Table 5 imply that a £1 minimum wage increase causes a 0.65 percentage point decline in the share of automatable employment available for low-skilled Asian workers (an elasticity of -0.148)[19].

Note on the Robustness to the Definition of Automatable and Offshorable Employment

Overall, the conclusions emanating from the share of employment analysis are robust to considering the US definitions of offshorable and automatable work (these analyses are documented in Appendix A). That is, that the main effects come from manufacturing, with the oldest workers, as well as males being the most affected.

A job is denoted as offshorable if it falls in the top tertile of offshorable work as defined by Equation (2). Conversely, a job is denoted as automatable if it falls in the top tertile of automatable work as defined in Equation (1). The focus on tertiles is somewhat arbitrary, so we also consider the sensitivity of this choice. Specifically, Appendix B documents the share of employment analysis for two

[19] These conclusions are supported when using the US proxies for automatable and offshorable employment (See Table A.5 in Appendix A).

alternative definitions that rely on a certain point on the offshorable or automatable distribution; namely i) top quartile and ii) top two quantiles. Once again, the overall narrative is pretty robust. We note that when considering the top quartile the coefficients are in general amplified, for the pooled and manufacturing analysis. Conversely, when we consider the top two quantiles the coefficients for the pooled and manufacturing analysis are attenuated. This pattern fits with the idea that it is the jobs that are the most 'automatable' or 'offshorable' that are the most vulnerable to minimum wage increases. That is, intuitively if a job's level of automatability and offshorability has information about the ease – and therefore cost – of automation or offshorability, these jobs will be the first jobs to disappear.

Table 6 also re-calculates the shares of employment analysis for full-time (35+hours) and part-time (<35 hours) workers separately. The former reframes the question to ask whether the shares of full-time automatable low-skilled jobs are more vulnerable than non-automatable full-time employment shares following a minimum wage increase. This allows us to comment on whether the effects that we find are driven by part-time or full-time work specifically. We note that for the shares of automatable employment analysis, it is the full-time analysis which is the most substantive. The same pattern holds for the share of offshorable employment analysis.

Effects on the Highest Skilled Group:

The hypothesis of this work is that minimum wage increases act as a price shock for low-skilled labour inputs. This in turn accelerates a firm's decision to automate or offshore tasks previously done by low-skilled individuals more quickly. We have also emphasised that there may be some job creation, to the extent that new technology or offshored activities need managing and trouble shooting. Therefore, a natural falsification for the shares of employment analysis emerges which re-calculates the shares of automatable and offshorable employment for the highest-skilled group[20]. Intuitively we define the highest-skilled group as those with a university degree who work in occupations in the highest income quantile.

Given our hypothesis we expect that minimum wage changes will have zero effect on the shares of employment of the highest skilled, or indeed positive effects if it is individuals of the highest skill that are hired as complements to the new technology or offshoring process. We document the results from these analyses in Appendix C. We note that almost all estimates are centred around zero, with no coefficient that is statistically significant from zero.

Re-Defining Minimum Wage

Our work relies on the QLFS, which consistently identifies twenty government regions across the period of analysis[21]. It is reasonable to hypothesise that minimum wage increases can have varying effects depending on the proportion of the population affected by increases. Therefore, we re-estimate Equation (4) and replace the minimum wage variable with the proportion of workers paid less per hour than the minimum wage[22] one year before the minimum wage was introduced. An advantage of this is that it creates variation at the area level, so we can replace our area specific time trends with area-specific year dummies, which is more conservative. That is, individual area-level linear time trends put a specific functional form on the trends in

[20] We have also considered a similar analysis for mid-skill level individuals (here, having at least an A level equivalent but not a third level qualification, such as a degree). We note that the effects are mostly centred around zero and weakly negative, suggesting that this group is also not significantly affected by minimum wage increases in terms of automatable job loss.

[21] These twenty regions are Tyne and Wear, rest of the North East, Greater Manchester, Merseyside, rest of the North West, South Yorkshire, West Yorkshire, Rest of Yorkshire and Humberside, East Midlands, West Midlands Metropolitan County, Rest of West Midlands, Eastern, Inner London, Outer London, South East, South West, Wales, Strathclyde, Rest of Scotland and Northern Ireland.

[22] As defined by hourly wage if reported, or wage per hour constructed from gross weekly wages divided by the number of usual weekly hours if not.

the shares of employment over time – they need to be either growing negatively or positively linearly. Area by year fixed effects do not put any assumptions on the nature of the differences experienced year on year, but absorb yearly heterogeneity that varies annually at the area level.

The results for this analysis are provided in Table 7. Overall, there is concordance between these results and what has gone before in many respects, but also some notable divergences. First, consistent with what has gone before, there are negative significant effects of the minimum wage on the share of automatable employment available to low-skilled workers. For example, for a 10-percentage point increase in the population covered by the minimum wage we would expect the share of automatable employment to fall by 0.52 percentage points. The effect is again most substantial in manufacturing (estimate equal to 0.1313), and small effects are detected in banking and finance, but notably the alternate measure of the minimum wage also identifies negative and significant effects for public administration, education and health.

The re-estimation of the share of automatable employment analysis also suggests that males and females are affected in roughly equal measures. Consistent with earlier analysis the effects on the shares of automatable employment for older workers (>=40 years) are larger than those expected for the middle age group (>=26 years and <=39 years), however now the youngest group (<25 years) exhibits the largest effects. Finally, Black workers again have the largest estimates, and the estimates for Asians are now greater than those for Whites. We note that it is difficult to say why these differences may occur but the sensitivity of the Asian coefficient may be caused by the cell size being small in the calculation of the shares of employment for some areas and industries. Additionally, the two proxies for minimum wage are different, and while low-skilled Asian workers in automatable employment may not be sensitive to the level of minimum wage increases they may be more sensitive to fraction of low-skilled workers affected in their area (which also captures the level of competition in the local market). Finally, we note that the variation which identifies the effects is also different. In the baseline model we rely on across time variation (allowing for area specific time effects), but in the model which considers the fraction of affected workers by area the variation comes from across areas.

Overall, the re-estimation supports the expectation that a higher minimum wage reduces the shares of automatable employment negatively and significantly, albeit the effects are modest.

The bottom panel of Table 7 displays the shares of offshorable jobs analysis. The estimates are more modest than documented in Table 2. Overall the pooled estimate is zero, and while the sub-analysis for manufacturing is still negative and significant, *all* of the workers in our sample would need to be affected to decrease the share of offshorable employment by 0.71 percentage points. Males and the oldest workers are again the worst affected in the re-analysis, however the effects are not economically meaningful. There are large differences between Blacks and other races in the re-analysis, which were not evident in Table 5. However, despite the differences in estimates a consistent narrative remains – the minimum wage accelerated the decline in the share of low-skilled offshorable jobs, however not to the same extent as it accelerated the decline in the share of low-skilled automatable jobs, and not to the extent that these declines are economically worrisome.

ASHE Replication[23]*:*

Table 8 utilizes ASHE[24] to reconsider our shares of employment analysis. The value of ASHE over the QLFS is that it has more reliable earnings data. This allows us to consider an analysis of low-paid workers with more certainty that they are directly affected by minimum wage increases, as compared with low-skilled workers where the distribution of earnings may be wider. In particular, we identify workers in the sample who are affected by minimum wage increases. We use a dummy variable which we assign equal to 1 if a person is below the minimum wage 1 year prior to an increase, and 0 otherwise. We then retain in our sample only those in the bottom 20% of the earnings distribution. So, the comparison group (dummy equals zero) are low-earnings workers who are on the minimum wage or higher prior to an increase.

Table 8 then relates the minimum wage to shares of automatable and offshorable work calculated for those in the bottom 20% of the earnings distribution. In this case the numerator is the number of individuals who are below the minimum wage and who are in automatable or offshorable work, and the denominator is the total employment in an industry, area and year for the bottom 20% of the earnings distribution. Consistent with previous analysis of the QLFS, area is based on official government region[25]. In the case of the gender and the age analysis, the numerators and denominators also vary by sex and age respectively[26].

---

[23] We note that we also tried to build Bartik style instruments for minimum wages in ASHE at the working area level. These instruments were never strong enough for identification in a 2SLS framework.
[24] Office for National Statistics. (2018). *Annual Survey of Hours and Earnings, 1997-2017: Secure Access*. [data collection]. *11th Edition.* UK Data Service. SN: 6689, http://doi.org/10.5255/UKDA-SN-6689-10
[25] We note that we also considered these analysis using lower-level work-based geographies and the conclusions do not change.
[26] ASHE does not record ethnicity.

Overall, Table 8 is consistent with the QLFS analysis for the shares of automatable employment analysis. That is, we find some evidence of negative effects of the minimum wage that are significant. In fact, in Table 8 there are many more industries with significant effects, and manufacturing still has the most substantive estimate. However, for the shares of offshorable analysis most of the estimates are centred around zero and not significant. Table 9 documents the same analysis by age and gender. Notably, consistent with earlier analysis, the oldest and the youngest workers are the most affected in the shares of automatable employment analysis. However, while the estimates do suggest significant declines in the shares of automatable employment for males, Table 9 suggests that females are affected more substantially (roughly double). Table 9 again suggests that there are no significant effects for the shares of offshorable employment across all strata.

Tables 8 and 9 relate the proportion of those who are affected by the minimum wage, in an area, industry and year, out of the universe of low-paid workers to the shares of employment described in the previous paragraph. Here, we are essentially looking to see whether there is a greater response in areas and industries to decreasing the shares of employment of offshorable and automatable jobs when there is a minimum wage increase if they are paying their employees below the new level. The value of this approach is that we create cross area variation so can include area and year fixed effects[27].

[27] We note that we also re-estimate the analyses described in Tables 8 and 9 and replaced the minimum wage variable with the proportion of workers paid less per hour than the minimum wage at the government region level one year before the minimum wage was introduced. As already discussed, this has the advantage of creating variation at the area level, so we can add area-specific year dummies, to the analysis. The results for this analysis are provided in Table F.1 in Appendix F. We note that overall these estimates suggest that there are negative effects of minimum wage increases on both the share of automatable employment and the share of offshorable employment, however the standard errors are too large for precise inference.

Effects on Remaining Employed.

Overall, the shares of employment analyses highlight the possibility that the absolute number of low-skilled automatable and offshorable jobs decreased in the last few decades in response to changes in the minimum wage. These effects are mostly concentrated in manufacturing. However, there are two reasons why we may get negative and significant effects in our shares of employment analysis. The first is job loss. However, it is also possible that the numerator is growing, implying that there are actually job gains in non-automatable or non-offshorable low-skilled jobs. That is, the evidence in the previous section does not necessarily imply that those previously in automatable jobs become unemployed.

To consider whether a higher minimum wage actually increases unemployment among low-skilled workers who were in automatable or offshorable employment in the first period relative to other workers, Table 10 reports estimates of Equation (7), which models the effects of the minimum wage on the probability a particular individual who holds an automatable or offshorable job is still employed in the second period, as opposed to being unemployed. This analysis is based on the Longitudinal Labour Force Survey.

Recall, that the effect is identified from the interaction between minimum wages and being in automatable or offshorable work. The baseline minimum wage effect is then not identified because of the inclusion of area by year fixed effects to allow for a more conservative analysis[28]. However, if identified, a negative base

---

[28] As already noted area by year fixed effects do not put any assumptions on the nature of the differences experienced year on year, but absorb yearly heterogeneity that varies annually at the area level.

minimum wage effect would imply that non-automatable (offshorable) workers also lose jobs. However, a positive base minimum wage effect would imply that non-automatable (offshorable) workers gain job security following a minimum wage increase.

From Table 10 Column (1), we find evidence of small but significant declines in the probability of remaining employed in the next period– and hence being unemployed – for those who were previously in either automatable or offshorable jobs as compared with those in non-automatable and non-offshorable jobs. Specifically, the estimates imply that a £1 minimum wage increase lowers the probability that a low-skilled worker in automatable employment remains employed by 0.15 percentage points, as compared with a comparable worker in non-automatable employment. For a person who is in offshorable employment this figure is higher, at 0.29 percentage points.

There is overall robustness in the estimated effects by industry, as compared with the shares of employment analyses, with the strongest declines evident in manufacturing. Specifically, the estimates imply that a £1 minimum wage increase lowers the probability that a low-skilled worker in automatable or offshorable employment in manufacturing remains employed by 0.27 and 0.41 percentage points respectively as compared with a comparable worker in non-automatable or non-offshorable employment. Notably, none of the estimates are significant in any other industry in the offshorable employment analysis. However, Table 10 Column (6) does suggest a small, negative and significant effect for low-skilled workers in banking and finance who hold automatable jobs. That is, a £1 minimum wage increase lowers the probability that a worker in this industry remains employed by 0.18 percentage points, as compared with a worker in non-automatable work in banking and finance.

The pattern of heterogeneity by demographic group is also similar to the estimated effects on shares earlier. First, males are more affected than females. This is evident from Table 11. In terms of magnitudes, the pooled estimates (Column (1)) for males imply that a £1 minimum wage increase lowers the probability that a low-skilled male in automatable employment remains employed by 0.25 percentage points, as compared with a male worker in non-automatable employment. This is 0.15 percentage points for low-skilled males in offshorable jobs. In manufacturing, these are more substantive: 0.49 and 0.33 percentage points for low-skilled workers in automatable and offshorable jobs respectively. In contrast, for females, Column (1) illustrates that the pooled estimates are no different from zero. However, the manufacturing estimates for females still imply negative and significant declines. That is, a £1 minimum wage increase lowers the probability of low-skilled females remaining in automatable employment by 0.26 percentage points as compared with those in non-automatable jobs. Notably, this is about 1/2 of the coefficient for males. There are no significant effects on shares of offshorable employment for females. However, the estimates do suggest similar losses for both genders working in low-skilled automatable banking and finance jobs (about 0.25 percentage points). None of the other estimates by industry in Table 10 are statistically significant.

Looking at effects by age in Table 12, the most adverse employment effects are for the oldest (greater than 40 years) and middle aged (older than 26 but younger than 39 years) groups. Specifically, there are small but significant declines in the probability of employment of 0.37 and 0.21 percentage points for low-skilled workers in automatable employment who are >=40 years and between 26 and 39 years respectively as compared with comparable persons in non-automatable employment. The largest effects are for those working in automatable employment in manufacturing with declines of 0.87 and 0.32 percentage points for these two groups respectively.

From Table 12, for those in low-skilled offshorable employment a £1 minimum wage increase, decreases the probability of being employed in the next period by 0.25 percentage points and 0.17 percentage points respectively for those aged >=40 years and between 26 and 39 years, as compared with comparable individuals working in non-offshorable employment. These conservative declines mask significant heterogeneity by industry. Specifically, in manufacturing for the same minimum wage increase these figures are 0.87 and 0.39 percentage points respectively. In addition, there are significant effects for those aged between 26 and 39 years in business and finance (a decrease of 0.42 percentage points for a £1 increase in the minimum wage).

Looking at the effects by race (Table 13) separately the pooled estimates are negative, with these effects being driven mainly by declines in manufacturing. For example, a £1 increase in the minimum wage reduces by 0.53 percentage points the overall probability of remaining employed in the next period for Black workers in offshorable employment, as compared with comparable Black workers in non-offshorable employment. However, the effect for manufacturing is 0.79 percentage points.

For Asian workers, the effects for manufacturing are never statistically significantly different from zero. However, there are substantive coefficients for low-skilled Asians in automatable employment in public administration, education and health (declines of 0.51 percentage points), and many other negative coefficients that are rendered not significant by imprecise standard errors (hotels and restaurants and transport and communications).

Effects on Occupational Switching

Table 14 reports results from an analysis where the dependent variable is equal to one if an individual stayed in the same occupation in the subsequent period, and zero otherwise. The sample includes those employed in period *t* and in the labour force in period *t*+1 who have valid occupation codes. Thus, the estimated effect of the minimum wage-routine interaction captures the change in job opportunities in the worker's initial occupation, with a "decline" captured in either unemployment *or* a change of occupations.

Second, while for the offshorable analysis the largest effects are still evident in manufacturing, for the automatable analysis manufacturing and banking and finance have comparable estimates, suggesting that higher minimum wages lead to some occupational switching among low-skilled workers in automatable jobs in these industries, in addition to transitions to unemployment. Specifically, the estimates imply that a £1 increase in the minimum wage leads to a 0.39 percentage point decrease in the probability of holding the same occupation in banking and finance for a low-skilled worker, as compared with a comparable worker in non-automatable employment. We note that occupation switches are arguably not without costs to either the employee or the employer. Third, workers between the ages of 26 and 39 years have the largest effects for both the automatable and offshorable analysis. Recall, that the oldest workers >=40 years were those who were most likely to lose their jobs in response to a minimum wage increase. This suggests middle-aged workers are more able to respond to higher minimum wages by finding an alternative occupation, as compared with older workers. Fourth, low-skilled males in both automatable and offshorable work are also more likely to switch jobs in response to a minimum wage increase, as compared with females. Finally, low-skilled White workers are most likely to switch jobs in response to a minimum wage increase, suggesting that White workers may also be more resilient to job loss with respect to job search.

Hours Effects

So far, the report has focused on analysis that reflects employment changes in low-skill automatable and offshorable employment in response to minimum wage changes. This suggests that the response from firms to a minimum wage increase is to move towards automation if labour is now relatively expensive and substitutable with technology. However, it is also possible that firms substitute with technology and decrease the hours of certain employees, rather than culling their jobs. We can consider this explicitly by re-estimating Equation (4) and relating minimum wage variation to an alternate dependent variable. Here, the dependent variable is the share of hours worked among low-skill workers in either automatable or offshorable employment, in a particular industry, area, and year. We also re-estimate Equation (7) with the difference in reported usual hours worked between this year and last year by an individual as the dependent variable. We focus only on those who are employed in the two periods (quarter 1 and quarter 5) and report non-zero working hours in both periods.

The results for the shares of hours analysis are reported in Table 15. Overall, the pooled estimates imply that minimum wage increases decrease shares of hours for low-skilled workers in automatable and offshorable jobs significantly. For example, a £1 minimum wage increase causes a 0.75 percentage point decrease in the share of hours in offshorable jobs done by low-skilled workers overall. The estimated declines in manufacturing are 0.79 and 1.48 percentage points for automatable and offshorable jobs respectively. Consistent with the share of employment analysis, the share of hours analysis suggests that males are most affected, along with the oldest workers.

The individual-level analysis considers the difference in the usual hours worked per week between period 1 and period 2. There are four quarters (one year) between the interview periods. The estimates are reported in Table 16 and suggest significant decreases in hours worked for those initially in automatable work following a minimum wage increase. Based on the pooled estimate, a £1 increase in the minimum wage generates a 0.40 percentage point decrease in hours worked for low-skilled individuals who held an automatable job in the previous period. The pooled effect for the offshorable analysis is zero.

In Table 16 the declines are negative, relatively substantive and statistically significant in manufacturing and banking and finance for low-skilled individuals in automatable work. Low-skilled individuals in manufacturing are the only group of offshorable workers that are affected by minimum wage increases in terms of hours worked as compared with comparable individuals in non-offshorable work. These effects are also pretty modest.

Turning to the sub-analysis by gender, males are more affected than females by endogenous technology adoption. Specifically, a £1 increase in the minimum wage is estimated to reduce hours worked for low-skilled males who held an automatable job in the previous period by 0.32 hours per week. For males in offshorable jobs the same figure is 0.51 hours per week.

Low-skilled automatable workers aged 26-39 are affected the most in the age sub-analysis. A £1 increase in the minimum wage causes a decrease of 0.86 hours per week, as compared with comparable workers in non-automatable employment. This figure is 0.65 hours for the same group in offshorable employment.

Considering the sub-analysis by race, low-skilled Black workers have the greatest decrease in hours following a minimum wage increase. However, low-skilled White workers also experience significant, albeit slightly lower, declines in hours. We note that an average minimum wage worker works approximately 26 hours a week and that the implication is that they still receive a wage increase, but are worse off than their comparable peers in non-automatable employment.

Exploring Dynamic Specifications for the Share of Employment Analysis

In the shares of employment analysis, the minimum wage is defined based on the average minimum wage in the current and past 11 months, itself averaged over the year, so that the absence of lagged effects allows effects that can arise over nearly two years. We have also augmented Equation (4) adding two lags of our minimum wage variable, replicating the analysis depicted in Table 2. The inclusion of lags allows for a period of adjustment to re-organize the factors of production away from labour and towards capital investments in technology. The results of these analysis are documented in Table 17. We note that none of the lags are significant. However, the main effects from the minimum wage still mainly come from the most immediate time period, implying that adjustments to the shares of automatable and offshorable employment occur predominately within 23 months following a minimum wage increase. This is clear if we consider Columns (1) and (2) which depict the pooled and manufacturing analysis respectively. Notably, the coefficients on the lags incorporated into theses analyses are closely centred around zero and never significant, with the main response to the minimum wage being captured by the most contemporary measure of the minimum wage[29].

Robustness to quarter chosen in the individual analysis:

Unfortunately, we cannot consider dynamics for the individual-level analysis given that we only observe individuals for five quarters, with our analysis drawing on measures of employment from the individuals first and last quarters. We have repeated the analysis described in Equation (7) and re cast t+1 as whether the person is employed when observed in their second, third or fourth quarter. We note here for brevity that the overall conclusions discussed in this report hold for these robustness analyses, with the exception of the analysis that considers only the change between the first and second quarter of the individual being observed. In this case, effects are centred around zero in the pooled analysis. Additionally, they are about 1/3 of the size for the manufacturing analysis. We tentatively note that this pattern is consistent with the idea that some time is needed to adjust to minimum wage changes, given that stronger effects are estimated when we consider employment outcomes with a one year gap.

Sub-analysis of High and Low Wage Low-skilled Manufacturing

So far, the results documented in Tables 2 through 13 point towards some job loss in automatable and offshorable jobs as a response to minimum wage increases. Notably, these effects are most substantive and economically meaningful in the

[29] We note that a limitation of this type of analysis is that we do not allow for anticipatory effects. That is, firms may begin to adjust at the policy announcement rather than at the minimum wage increase. In a separate analysis we have checked robustness to adding anticipatory effects to Table 14, and separately to our baseline models that do not consider any lags. We note here for brevity that the anticipatory effects are never significant, but are negative. Adding anticipatory effects does attenuate the baseline contemporary effect by about one third (specifically between 25% and 35%), an order which is roughly subsumed into the newly included forward co-efficient. So, we are not confident ruling out anticipatory effects nor can we confirm their existence.

manufacturing industry. A natural test of the robustness of these results is to consider additional sub-analysis by low-wage and high-wage low-skill workers in manufacturing. That is, if the responses we find are indeed endogenous changes owed to minimum wage hikes, we would expect the greatest effects to be felt by the lowest-wage workers.

For each low-skill occupation within manufacturing, we compute average wages from the 1994-2017 QLFS. The low-wage subsample is then defined as the bottom tertile of occupations in this distribution, and the high-wage subsample as the top tertile. These definitions are matched to the data used for the analyses in Tables 2-13 and separate analyses of Equations (4) and (7) are conducted for the two sub-samples. Examples of the low-wage low-skill occupations in manufacturing are elementary cleaners, elementary process plant occupations and plant and machine operatives. Examples of high-wage low-skill occupations in manufacturing are skilled trades and sales-related occupations.

The results for the manufacturing high and low-wage share of employment sub-analysis are documented in Table 18. Overall, these estimates highlight that minimum wage increases negatively and substantively affect the shares of employment and the probability of being employed for the lowest-paid low-skilled workers. However, there is little evidence of any effects for those who are paid the highest wages for low-skilled automatable and offshorable work. For example, a £1 minimum wage increase causes a 1.24 percentage point decrease in the share of employment in automatable jobs done by the lowest-paid low-skilled workers overall. However, the coefficient for the highest-paid workers is centred close to zero and not significant in the pooled analysis. The analysis for the share of offshorable employment exhibits a similar pattern: a £1 minimum wage increase causes a 0.59

percentage point decrease in the share of employment in offshorable jobs done by the lowest-paid low-skilled workers overall. Conversely, the pooled estimate for the highest paid low-skilled workers is positive but not significant.

Table 18 also highlights that it is the shares of automatable employment for the oldest low-paid low-skill workers, as well as Whites and males that are the most affected by minimum wage increases. However, the pattern is different for the shares of offshorable employment analysis. Specifically, it is the shares of offshorable analysis for low-skilled low-educated workers aged between 26 and 39 years, Blacks and males where the biggest effects are demonstrated. Consistent with the full sample analysis, the effects for the low-skilled lowest-paid shares of employment analysis are largest when we consider automatable employment.

Table 19 documents the sub-analysis, which explicitly models the probability of being employed in the next period for low-skilled automatable (offshorable) workers in manufacturing as compared with those in non-automatable (non-offshorable) jobs. For low-wage jobs, we find significant negative effects for both the offshorable and automatable pooled analysis. For example, a £1 minimum wage increase reduces the probability that a low-skilled low-wage worker in automatable employment keeps their job in the next period by 0.90 percentage points as compared with a worker in non-automatable employment. For the offshorable analysis this figure is 0.47 percentage points.

Interestingly, contrary to the full sample analysis, low-skilled low-wage females in automatable jobs are more likely to lose employment in the next period, compared with males. That is, the results for females imply that females are less likely to be employed in the next period by 0.55 percentage points if they are in automatable work as compared with comparable females in non-automatable work. This compares with 0.35 percentage points for males.

Consistent with earlier analysis automatable workers over the age of 40 are the most affected by minimum wage increases. That is, a £1 minimum wage increase reduces the probability that a worker in this group keeps their job in the next period by 1.11 percentage points as compared with a comparable worker in non-automatable employment. There are also substantive effects for low-skilled low-educated automatable workers aged between 26 and 39 years, Whites and Blacks. The offshorable sub-analysis reveals that males, the oldest workers and Whites are the most affected by minimum wage changes.

Overall the individual level analysis, together with the shares of employment analysis, provides evidence consistent with the narrative that it is the lowest-paid workers who are most affected by a firm's decisions to move towards automation or offshoring as a response to a minimum wage increase. In general, the effects for the highest paid low-skilled workers are centred closer to zero and are not statistically significant.

Comment on Split by Services

The analysis in this report relies on industry codes which have a very heterogeneous grouping of 'other services'. We note that we have probed for heterogeneity within this group, and tentatively, given at times small samples, can conclude that there is no evidence of endogenous automation or offshoring in these services in response to changes in the minimum wage.

Specifically, we ran separate regressions for hairdressing, elementary cleaning occupations, and elementary personal service occupations. Finding no effects is intuitive as these occupations require an employee to be in a specific geographic location (ruling out offshoring potential) and carry out tasks in an unpredictable sequence (ruling out automation). We note that we did not have enough observations to explore whether endogenous automation or offshoring was affecting the number of call centre positions.

Going Forward

The definitions of automation and offshorability used in this work follow Autor and Dorn (2013) and Firpo, Fortin, and Lemieux (2011) respectively. These are intuitive definitions for a retrospective analysis, given the occupations identified as automatable and offshorable appear reasonable and very credible. In general, we expect that the definition of offshorable is likely to be representative for decades to come. That is, a job cannot be offshored to the extent that people need to be physically present to get their tasks done. However, it is likely that more jobs get offshored as employees become more comfortable using technology to contact their teams remotely, or customers being more accustomed to being supported remotely. These are mainly office support or customer service roles, and are still captured by the definition utilized in this work.

There is however a seismic change on the horizon with respect to the jobs that will be automated in the near future. That is, many more occupations that employ low-skill workers are on track to be automated, even if they are not currently labeled as 'automatable' in this analysis. For example, face-to-face service occupations are classified as non-automatable in this analysis, however, already there is a hotel in Tokyo that is staffed by robots[30] and a restaurant in Germany that relies on a robot

[30] Multi-lingual robots provide the receptionist's duties, a robotic arm tends to the luggage room and porter robots carry luggage to room. Lost keys are not an issue as rooms respond to face recognition software.

chef[31]. We note that it is no surprise that workers are being replaced readily in Japan given their current blue-collar labour shortage. However, firms also can endogenously choose to automate if the labour costs get too high. Therefore, to inform on the type of automation we can expect going forward, we reviewed specific searches on Google Patents[32].

Specifically, we selected ten occupations, currently labelled as non-automatable, from the QLFS 2017 data that represent the largest proportion of individuals with low skill. We then searched Google Patents for search terms that would relate to the automation of part or all of this occupation. Specifically, we searched for variants of the occupation name, plus variants of the word 'robot.' For example, for hairdresser we searched for *hair* +robot*.* Next, we read through the title, abstract and when necessary (if a conclusion could not be reached from the abstract) a full description of the patent. This allows us to garner patterns in the type of technology that is being developed that can substitute for the tasks currently being done by low-skilled workers. That is, our interest is in technology for robot workers only. Comments on this review are provided in Table 20.

We note that a few important conclusions emerge from Table 20. First, jobs where inter-personal skills are required in order to gauge the specific tasks that are needed are unlikely to be automated. Childcare and hairdressing both require engagement with people in unpredictable sequences which are not easily replicated by machines and cannot be easily aided by the customer. Second, there is a lot of R&D

[31] Huis Ten Bosch: Here robots prepare food, with one robot being in charge of making pancakes, it mixes batter, and uses robotic arms to flip the pancakes before dressing them.

[32] Google Patents is a search engine that contains data for patents filed in the United States, Europe, Japan, China, South Korea, WIPO, Russia, Germany, The United Kingdom, Canada, France, Spain, Belgium, Denmark, Finland, Luxembourg, and the Netherlands

into technology for other jobs that historically require interpersonal reaction but there is a more predictable sequence of events. These jobs include waiting tables and bartending. The technology here has had some success, with some examples of successful substitution by robots. We envisage, however, that these developments will progress resulting in a polarization, with human employees being kept in establishments where a personal interaction with a waiter or bartender holds some value and robots being utilized where it does not. Third, there is a lot of R&D in areas that customers may care less about whether the job is done by a robot or a human. These include delivery driver and bricklayer. So, the value to the customer of having a human carry out these roles is zero. In both these areas there have been significant developments to the extent we may expect a cull of jobs in the next decade accelerated by relatively high minimum wages.

Overall, there seem to be roughly three types of occupations with respect to automation potential. The first group are occupations where empathy and other soft skills are valued and a person cares about who carries out the work. These occupations are unlikely to be automated. The second are occupations where in some cases a person may care who carries out the service, whereas in others they do not. An example is waiting where a good host may be part of the experience in fine dining but not in a takeaway. Again, people skills will be of great value for the jobs that remain. We envisage that some of these jobs will be automated. Third, are the jobs where there is no added value whether the work is carried out by a robot or a human. These are the jobs for humans that will decline the most sharply.

Technology is advancing to take on jobs that were not previously defined as automatable, such as driver and bartender. This will undoubtedly create new work as there is an ongoing need for workers to troubleshoot and maintain the new technology, as well as to carry out aspects of the task that the robot cannot (for example, instructing customers on how to interact with their robot bartender). In the past, the adoption of technologies has always led to the emergence of new jobs to replace those that are being replaced. If this occurs we would expect that these new jobs will require different skills. As described above soft skills and empathy will be of value in many of the low-skilled jobs that are not threatened by automation. However, for replacement jobs that emerge, it is likely that they will involve interacting with the new technology in some respect. Older workers may find it the hardest to acquire these new skills, and as emphasized in the results documented here, this is the group most vulnerable to job loss from automation. Finally, we caution against relying on trends of the past to predict what will happen in the future. That is, just because all jobs lost have been replaced with new jobs in the past does not mean that this will continue to occur in the future. Replacement at these levels will become less likely as machines continue to learn. So, there is a role for policy to play in ongoing monitoring of trends, and to give due consideration as to how the rents earned by machines should be re-distributed within society as technology adoption accelerates.

Conclusions:

In a landscape where the National Living Wage (NLW) in the UK is £7.83 and is set to rise to 60 per cent of median hourly earnings, around £8.60, by 2020, we explore whether previous minimum wage increases have affected the employment possibilities for workers relying on automatable or offshorable employment. Notably, automation and offshorability have been the two dominant forces that have threatened jobs in the UK in the last decades. Drawing on Quarterly Labour Force Survey data (QLFS) from 1994 – 2017 and classifying each occupation as either automatable/non-automatable and offshorable/non-offshorable, we consistently highlight that minimum wage increases decrease the shares of both offshorable and automatable employment following a minimum wage increase. However, these effects are very modest. For an increase in the minimum wage from £7.50 to £8.50 the implied elasticities are -0.055 (around 27,000 jobs) and -0.034 (around 17,000 jobs) for the shares of automatable and offshorable employment analysis respectively. These aggregate effects mask larger changes for manufacturing, older workers, males and Black workers. We do note that only the conclusions from our shares of automatable employment analysis are robust to a replication in ASHE.

A consistent narrative emerges for an analysis which considers the likelihood a low-skilled worker in automatable or offshorable employment remains employed in the next period as compared with a low-skilled worker in non-automatable employment following a minimum wage increase. That is, the aggregate effects are very modest but sub-analysis reveals that low-skilled workers in manufacturing are the most vulnerable to the loss of automatable and offshorable work, as well as low-skilled males, Black and older workers. We also highlight that low-skilled workers in automatable or offshorable employment are more likely to switch jobs in the next period following a minimum wage increase. Those for offshorable employment are not.

Overall, the empirical analysis suggests that firms may re-assess their production processes following minimum wage increases, but so far endogenous substitution has been limited. The forecasts in this work also highlight that substitution should continue to be modest up to £8.50. However, these conclusions rely on both the classifications and costs of automatable and offshorable work remaining static. We have discussed that this is unlikely for automation. First, the costs of technology continue to fall. Second, drawing on a review of Google patents, supplemented with examples of robotics that are actively substituting for workers today, we have provided evidence that additional low-skill jobs are on stream to be automated in the future, such as taxi driver and bricklayer. These jobs lost to automation in the future will be met with the creation of new jobs that require an entirely different set of skills. We do not know if these will be in equal number to those lost. Just because all jobs lost have been replaced with new jobs in the past does not mean that this will continue to occur in the future. Replacement at these levels will become less likely as machines increasingly undertake more complex tasks. There is a role for policy to play in ongoing monitoring of trends, and to give due consideration as to how the rents earned by machines are distributed.

References:

1. Aaronson, Daniel, Brian J. Phelan. 2017. "Wage Shocks and the Technological Substitution of Low-Wage Jobs." The Economic Journal. June.
2. Autor, David H., Alan Manning, Christopher L. Smith. 2016. "The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment." American Economic Journal: Applied Economics, Vol. 8, No. 1, January, pp. 58-99.
3. Autor, David H., David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review, Vol. 103, No. 5, August, pp. 1553-97.
4. Autor, David, David Dorn, and Gordon Hanson. 2015. "Untangling Trade and Technology: Evidence from Local Labor Markets." Economic Journal, Vol. 125, No. 584, May, pp 621-46.
5. Bewley, Helen, David Wilkinson. 2015. "The Impact of the National Minimum Wage on Employment and Hours. National Institute of Economic and Social Research. February.
6. de Linde Leonard, Megan, T. D. Stanley, Hristos Doucouliagos. 2014. "Does the UK Minimum Wage Reduce Employment? A Meta-Regression Analysis." British Journal of Industrial Relations, Vol. 52, Issue 3, pp. 499–520.
7. Dickens, Richard, Rebecca Riley, and David Wilkinson. 2015."A Re-examination of the Impact of the UK National Minimum Wage on Employment." Economica, Vol. 82, No. 328, pp. 841-864.
8. DiNardo, John, Nicole Fortin, Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." Econometrica, Vol. 64, No. 5, September, pp. 1001-44.
9. Fidrmuc, Jan, J. D. Tena. 2013. "National Minimum Wage and Employment of Young Workers in the UK" CESifo Working Paper Series, No. 4286, June.
10. Firpo, Sergio, Nicole M. Fortin, Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure" IZA Discussion Paper, No. 5542, February.
11. Graetz, Georg, Guy Michaels. 2015. "Robots At Work" CEP Discussion Paper, No 1335, March.
12. Graetz, Georg, Guy Michaels. 2017. "Is Modern Technology Responsible for Jobless Recoveries?" American Economic Review, Vol. 107, No.. 5, May, pp. 168-73.
13. Hafner, Marco, Jirka Taylor, Paulina Pankowska, Martin Stepanek, Shanthi Nataraj, Christian van Stolk. 2017. "The Impact of The National Minimum Wage On Employment: A Meta-Analysis" RAND Europe. Available at: https://www.rand.org/content/dam/rand/pubs/research_reports/RR1800/RR1807/RA ND_RR1807.pdf.
14. Lordan, Grace, David Neumark. 2017. "People Versus Machines: The Impact of Minimum Wages on Automatable Jobs" NBER Working Paper, No. 23667, August.
15. Lordan, Grace, Jorn-Steffen Pischke. 2016. "Does Rosie like riveting? Male and female occupational choices" NBER working paper, 22495, August.

16. Machin, Stephen, Joan Wilson. 2004. "Minimum wages in a low-wage labour market: Care homes in the UK" Economic Journal, Vol. 114, Issue 494.
17. Office for National Statistics Social Survey Division, Northern Ireland Statistics and Research Agency. Central Survey Unit. (2018). *Labour Force Survey Household Datasets, 2002-2017: Secure Access*. *3rd Edition.* UK Data Service. SN: 7674, http://doi.org/10.5255/UKDA-SN-7674-3
18. Papps, Kerry, P. Gregg. 2014. "Beyond the wage: Changes in employment and compensation patterns in response to the national minimum wage." Low Pay Commission.
19. Simon, Kosali Ilayperuma, Robert Kaestner. 2004. "Do Minimum Wages Affect Non-Wage Job Attributes? Evidence On Fringe Benefits." Industrial and Labor Relations Review, Vol. 58, No. 1, pp. 52-70.
20. Sorkin, Isaac. 2015. "Are There Long-Run Effects of the Minimum Wage?" Review of Economic Dynamics, Vol. 18, No. 2, April, pp. 306-33.
21. Stewart, Mark B. 2004. "The employment effects of the national minimum wage" *Economic Journal,* Vol. 114, Issue 494, March.

Table 1: Examples of Automatable and Offshorable Jobs

Automatable	Offshorable
Elementary administration occupations	Food Preparation Trades
Elementary process plant occupations	Textile and Garments Trades
Assemblers and Routine Operatives	Call Center Occupations
Food Preparation Trades	Assemblers and Routine Operatives
Administrative Occupations – Records	Plant and Machine Operators
Non-Automatable	Non-offshorable
Transport Drivers and Operatives	Housekeeping Occupations
Personal Service Occupations NEC	Childcare and Personal Services
Metal Machining, Fitting and Instrument Making Trades	Healthcare and Related Personal Services
Sales Related Occupations	Building Trades
Customer Service Occupations	Hairdressers and Related Occupations

Table 2: Shares of Employment Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0024**	**-0.0058**	-0.0012	-0.0008	-0.0026	**-0.0021**	0.0009	-0.0006
	(0.0007)	**(0.0011)**	(0.0011)	(0.0019)	(0.0016)	**(0.0012)**	(0.0015)	(0.0012)
N	4320	480	480	480	480	480	480	480
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Offshorable Employment								
MinWage	**-0.0015**	**-0.0034**	-0.0001	-0.0011	-0.0021	-0.0000	0.0013	-0.0007
	(0.0006)	**(0.0012)**	(0.0013)	(0.0012)	(0.0014)	(0.0005)	(0.0012)	(0.0012)
N	4320	480	480	480	480	480	480	480

Notes: OLS coefficient estimates are reported, with standard errors in parentheses. Figures in bold are significant at the 5% level. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who have a GCSE equivalent or less and work in an occupation that is in the lowest quantile of the income distribution. The definition of automatable employment is created from variables in the UK Skills and Employment Surveys Series Dataset. A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of offshorable employment is calculated in the same manner. All regressions include area fixed effects and area specific time trends. Regressions also include: Area level demographics that vary over time: average age, education, gender; Occupation demographics measured at the area/industry/year level: average age, education, gender. The pooled regression also has industry fixed effects. The minimum wage is measured in 2015 prices.

Table 3: Shares of Employment Estimates: Gender Specific

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Males								
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0032**	**-0.0084**	-0.0001	-0.0018	-0.0003	**-0.0028**	0.0022	-0.0017
	(0.0008)	**(0.0015)**	(0.0012)	(0.0014)	(0.0017)	**(0.0011)**	(0.0019)	(0.0014)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0023**	**-0.0043**	0.0003	-0.0007	-0.0012	-0.0018	-0.0023	-0.0007
	(0.0008)	**(0.0015)**	(0.0011)	(0.0011)	(0.0019)	(0.0011)	(0.0019)	(0.0002)
N	4320	480	480	480	480	480	480	480
Females								
Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0009	**-0.0032**	-0.0006	-0.0017	-0.0006	-0.0018	-0.0007	-0.0016
	(0.0008)	**(0.0015)**	(0.0014)	(0.0014)	(0.0016)	(0.0019)	(0.0018)	(0.0016)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0004	-0.0017	-0.0006	-0.0016	-0.0003	-0.0013	-0.0009	-0.0016
	(0.0007)	(0.0017)	(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0012)	(0.0018)
N	4320	480	480	480	480	480	480	480

See notes to Table 2

Table 4: Shares of Employment Estimates: Age Specific

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
>= 40 Years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0060**	**-0.0105**	-0.0025	-0.0017	-0.0016	0.0003	-0.0015	-0.0014
	(0.0007)	**(0.0014)**	(0.0013)	(0.0017)	(0.0015)	(0.0012)	(0.0011)	(0.0016)
N	4320	480	480	480	480	480	480	480
>= 40 Years Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0026**	**-0.0061**	-0.0014	-0.0013	-0.0013	-0.0003	-0.0036	-0.0002
	(0.0008)	**(0.0013)**	(0.0015)	(0.0011)	(0.0003)	(0.0009)	(0.0023)	(0.0003)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0039**	**-0.0062**	0.0016	0.0015	-0.0017	**-0.0038**	-0.0005	-0.0006
	(0.0008)	**(0.0018)**	(0.0014)	(0.0018)	(0.0014)	**(0.0018)**	(0.0017)	(0.0004)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	**-0.0036**	-0.0014	-0.0009	-0.0000	-0.0006	0.0007	-0.0005
	(0.0006)	**(0.0012)**	(0.0013)	(0.0014)	(0.0015)	(0.0014)	(0.0017)	(0.0017)
N	4320	480	480	480	480	480	480	480
<25 years Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0012	-0.0006	-0.0002	-0.0008	-0.0006	-0.0011	-0.0031	-0.0002
	(0.0007)	(0.0014)	(0.0011)	(0.0015)	(0.0012)	(0.0016)	(0.0016)	(0.0011)
N	3263	426	383	431	383	442	443	427
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0003	-0.0003	0.0001	0.0001	-0.0003	-0.0023	-0.0012	-0.0006
	(0.0008)	(0.0015)	(0.0011)	(0.0014)	(0.0011)	(0.0012)	(0.0012)	(0.0013)
N	3263	426	383	431	383	442	443	427

See notes to table 2

Table 5: Shares of Employment Estimates Race Specific

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
White Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0029**	**-0.0071**	-0.0011	-0.0013	-0.0012	-0.0014	0.0026	-0.0000
	(0.0009)	**(0.0019)**	(0.0015)	(0.0014)	(0.0019)	(0.0014)	(0.0014)	(0.0015)
N	4320	480	480	480	480	480	480	480
White Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0017**	**-0.0045**	-0.0015	0.0016	-0.0013	0.0005	0.0007	-0.0012
	(0.0008)	**(0.0014)**	(0.0012)	(0.0014)	(0.0012)	(0.0014)	(0.0020)	(0.0017)
N	4320	480	480	480	480	480	480	480
Black Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0060**	**-0.0106**	0.0000	0.0013	-0.0000	0.0000	-0.0008	-0.0014
	(0.0018)	**(0.0025)**	(0.0020)	(0.0024)	(0.0026)	(0.0024)	(0.0023)	(0.0023)
N	3612	452	440	451	445	455	459	443
Black Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0012	-0.0031	0.0000	-0.0008	-0.0039	0.0000	0.0010	0.0020
	(0.0017)	(0.0029)	(0.0023)	(0.0025)	(0.0022)	(0.0027)	(0.0026)	(0.0025)
N	3612	452	440	451	445	455	459	443
Asian Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0013	-0.0021	0.0006	-0.0031	-0.0000	-0.0055	0.0017	-0.0040
	(0.0018)	(0.0030)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0039)	(0.0029)
N	3486	370	396	358	369	383	390	410
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0002	-0.0002	0.0002	-0.0003	-0.0022	-0.0034	-0.0018	-0.0008
	(0.0035)	(0.0032)	(0.0036)	(0.0037)	(0.0039)	(0.0034)	(0.0035)	(0.0035)
N	3486	370	396	358	369	383	390	410

Table 6: Shares of Employment Estimates: Full Time, Part Time and Overtime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Full-Time	Dependent Variable = Share of Automatable Employment							
Min Wage	**-0.0019**	**-0.0060**	-0.0002	-0.0000	-0.0015	-0.0017	0.0011	0.0000
	(0.0009)	**(0.0013)**	(0.0010)	(0.0014)	(0.0008)	(0.0013)	(0.0013)	(0.0008)
N	4320	480	480	480	480	480	480	480
Full-Time	Dependent Variable = Share of Offshorable Employment							
Min Wage	**-0.0016**	**-0.0019**	0.0005	-0.0015	-0.0010	-0.0000	0.0013	-0.0010
	(0.0007)	**(0.0010)**	(0.0009)	(0.0013)	(0.0013)	(0.0005)	(0.0012)	(0.0010)
N	4320	480	480	480	480	480	480	480
Part Time	Dependent Variable = Share of Automatable Employment							
Min Wage	-0.0014	-0.0020	-0.0011	-0.0017	-0.0023	-0.0004	-0.0000	0.0008
	(0.0011)	(0.0016)	(0.0012)	(0.0012)	(0.0012)	(0.0009)	(0.0008)	(0.0006)
N	4320	480	480	48014	480	480	480	480
Part Time	Dependent Variable = Share of Offshorable Employment							
Min Wage	-0.0007	**-0.0031**	0.0008	-0.0000	0.0007	-0.0013	-0.0000	0.0007
	(0.0011)	**(0.0013)**	(0.0010)	(0.0012)	(0.0009)	(0.0012)	(0.0011)	(0.0012)
N	4320	480	480	480	480	480	480	480

Table 7: Alternate Minimum Wage Definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0519**	**-0.1313**	0.0016	0.0000	0.0050	**-0.0031**	**-0.0100**	0.0031
	(0.0012)	**(0.0016)**	(0.0017)	(0.0019)	(0.0016)	**(0.0016)**	**(0.0020)**	(0.0017)
N	4320	480	480	480	480	480	480	480
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage	**-0.0197**	**-0.0215**	**-0.0416**	**-0.0250**	**-0.0519**	**-0.0287**	**-0.0740**	**-0.0429**
	(0.0011)	**(0.0011)**	**(0.0012)**	**(0.0013)**	**(0.0017)**	**(0.0012)**	**(0.0026)**	**(0.0021)**
N	4320	4320	4320	4320	3263	4320	3612	3486
Dependent Variable = Share of Offshorable Employment								
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Min Wage	-0.0000	**-0.0071**	0.0041	0.0000	0.0001	**-0.0031**	0.0028	-0.0027
	(0.0010)	**(0.0019)**	(0.0018)	(0.0019)	(0.0020)	**(0.0015)**	(0.0017)	(0.0014)
N	4320	480	480	480	480	480	480	480
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage	**-0.0042**	0.0026	**-0.0030**	-0.0021	0.0000	-0.0009	**-0.0144**	-0.0032
	(0.0015)	(0.0018)	**(0.0014)**	(0.0018)	(0.0017)	(0.0014)	**(0.0015)**	(0.0019)
N	4320	4320	4320	4320	3263	4320	3612	3486

Table 8: ASHE replication for Low Paid Workers: Share of employment analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Manufacturing	Utilities	Wholesale	Transport	Services	Professional Services	Admin Services	Public Admin
Min Wage *Automatable	**-0.0089**	**-0.0321**	-0.0169	**-0.0131**	**-0.0057**	**-0.0184**	-0.0008	**-0.0188**	**-0.0233**
	(0.0016)	**(0.0034)**	(0.0114)	**(0.0043)**	**(0.0023)**	**(0.0027)**	(0.0068)	**(0.0035)**	**(0.0034)**
N	2036	198	198	198	198	198	198	198	198
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Pooled	Manufacturing	Utilities	Wholesale	Transport	Services	Professional Services	Admin Services	Public Admin
Min Wage* Offshorable	-0.0006	-0.0005	-0.0007	**-0.0063**	0.0004	0.0008	-0.0006	-0.0012	0.0003
	(0.0005)	(0.0002)	(0.0010)	**(0.0007)**	(0.0001)	(0.0005)	(0.0017)	(0.0007)	(0.0007)
N	2036	198	198	198	198	198	198	198	198

Notes: Data are from the 1998- 2015 ASHE surveys. OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who are in the bottom 20% of the income distribution in any given year. A person is defined as a minimum wage worker if they were paid below the minimum wage one year before an increase. The definition of automatable employment is created from variables in the UK Skills and Employment Surveys Series Dataset. A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of offshorable employment is calculated in the same manner. All regressions include area fixed effects and area specific time trends. The pooled regression also has industry fixed effects. The minimum wage is measured in 2015 prices.

Table 9: ASHE replication for Low Paid Workers: Share of employment analysis by Strata

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	>=40 years	<40 years and >25 years	<25 years	Male	Female
Min Wage *Automatable	**-0.0089**	**-0.0081**	-0.0056	**-0.0136**	**-0.0055**	**-0.0093**
	(0.0016)	**(0.0019)**	(0.0034)	**(0.0037)**	**(0.0019)**	**(0.0021)**
N	2036	2036	2036	2036	2036	2036
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	>=40 years	<40 years and >25 years	<25 years	Male	Female
Min Wage* Offshorable	0.0006	0.0005	0.0009	0.0001	0.0004	0.0006
	(0.0005)	(0.0008)	(0.0005)	(0.0008)	(0.0004)	(0.0008)
N	2036	2036	2036	2036	2036	2036

Notes: Data are from the 1998- 2015 ASHE surveys. OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who are in the bottom 20% of the income distribution in any given year. A person is defined as a minimum wage worker if they were paid below the minimum wage one year before an increase. The definition of automatable employment is created from variables in the UK Skills and Employment Surveys Series Dataset. A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of offshorable employment is calculated in the same manner. All regressions include area fixed effects, industry fixed effects and area specific time trends. The minimum wage is measured in 2015 prices.

Table 10: Individual Level Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking& Finance	P Admin Educ and Health	Other Services
Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage *Automatable	**-0.0015**	**-0.0029**	-0.0013	0.0013	-0.0006	**-0.0018**	-0.0011	-0.0006
	(0.0005)	**(0.0005)**	(0.0018)	(0.0013)	(0.0016)	**(0.0007)**	(0.0007)	(0.0015)
N	440614	75965	20858	58546	45190	60430	108347	37373
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking & Finance	Public Admin Educ and Health	Other Services
Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage* Offshorable	**-0.0029**	**-0.0041**	-0.0007	0.0008	-0.0004	-0.0003	-0.0005	-0.0015
	(0.0007)	**(0.0006)**	(0.0014)	(0.0011)	(0.0015)	(0.0008)	(0.0003)	(0.0011)
N	440614	75965	20858	58546	45190	60430	108347	37373

Notes: OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who have a GCSE equivalent or less and work in an occupation that is in the lowest quantile of the income distribution. The definition of automatable employment is created from variables in the UK Skills and Employment Surveys Series Dataset. A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of offshorable employment is calculated in the same manner. All regressions include area crossed by year fixed effects. The pooled regression also has industry fixed effects. The minimum wage is measured in 2015 prices.

.

Table 11: Individual Level Estimates: Gender Specific

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
Males								
Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	**-0.0025**	**-0.0049**	-0.0014	0.0009	0.0005	**-0.0025**	-0.0012	0.0007
*Automatable	**(0.0004)**	**(0.0008)**	(0.0022)	(0.0018)	(0.0007)	**(0.0010)**	(0.0011)	(0.0031)
N	249302	49097	15500	35345	29167	33387	35928	25611
Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	-0.0005	**-0.0033**	-0.0006	0.0004	0.0002	-0.0018	-0.0016	-0.0004
*Offshorable	(0.0006)	**(0.0009)**	(0.0030)	(0.0018)	(0.0008)	(0.0011)	(0.0010)	(0.0016)
N	249302	49097	15500	35345	29167	33387	35928	25611
Females								
Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	-0.0001	**-0.0026**	0.0003	0.0015	0.0012	-0.0017	-0.0013	-0.0008
*Automatable	(0.0009)	**(0.0010)**	(0.0027)	(0.0015)	(0.0008)	(0.0011)	(0.0007)	(0.0020)
N	191312	26868	5358	23201	15993	27043	72419	11762
Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	-0.0004	-0.0005	-0.0019	0.0004	-0.0000	-0.0011	-0.0015	-0.0004
*Offshorable	(0.0005)	(0.0005)	(0.0018)	(0.0022)	(0.0009)	(0.0008)	(0.0009)	(0.0012)
N	191312	26868	5358	23201	15993	27043	72419	11762

Table 12: Individual Level Estimates: Age Specific

	(1) Pooled	(2) Manufacturing	(3) Construction	(4) Hotels and Restaurants	(5) Transport and Communication	(6) Banking & Finance	(7) P Adm Educ & Health	(8) Other Services
>= 40 Years Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	**-0.0037**	**-0.0087**	-0.0023	0.0020	-0.0012	-0.0030	**-0.0017**	0.0013
*Automatable	**(0.0004)**	**(0.0006)**	(0.0030)	(0.0020)	(0.0017)	(0.0019)	**(0.0008)**	(0.0019)
N	211312	40560	9636	24065	28711	22378	45870	13410
>= 40 Years Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	**-0.0025**	**-0.0029**	-0.0003	0.0027	-0.0013	-0.0033	-0.0010	-0.0009
*Offshorable	**(0.0007)**	**(0.0007)**	(0.0034)	(0.0022)	(0.0018)	(0.0020)	(0.0012)	(0.0013)
N	211312	40560	9636	24065	28711	22378	45870	13410
>25 years and <40 years Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	**-0.0021**	**-0.0032**	0.0003	0.0001	0.0014	-0.0042	-0.0008	-0.0050
*Automatable	**(0.0006)**	**(0.0011)**	(0.0019)	(0.0031)	(0.0007)	(0.0008)	(0.0015)	(0.0032)
N	196397	32436	9912	28804	15179	34140	52525	18041
>25 years and <40 years Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	**-0.0017**	**-0.0039**	0.0011	0.0002	0.0013	0.0010	-0.0001	0.0023
*Offshorable	**(0.0006)**	**(0.0009)**	(0.0014)	(0.0028)	(0.0008)	(0.0008)	(0.0012)	(0.0024)
N	196397	32436	9912	28804	15179	34140	52525	18041
<25 years Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	-0.0014	-0.0021	0.0009	0.0008	0.0031	0.0006	-0.0018	-0.0037
*Automatable	(0.0019)	(0.0035)	(0.0042)	(0.0083)	(0.0036)	(0.0020)	(0.0052)	(0.0036)
N	32905	2969	1310	5677	1300	3912	9952	5922
<25 years Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	-0.0022	0.0014	0.0002	0.0037	0.0033	-0.0013	-0.0009	0.0026
*Automatable	(0.0016)	(0.0030)	(0.0031)	(0.0072)	(0.0033)	(0.0021)	(0.0033)	(0.0043)
N	32905	2969	1310	5677	1300	3912	9952	5922

Table 13: Individual Level Estimates: Race Specific

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
White Dependent Variable = Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	**-0.0018**	**-0.0039**	-0.0033	0.0021	-0.0019	**-0.0033**	-0.0008	-0.0005
*Automatable	**(0.0006)**	**(0.0007)**	(0.0020)	(0.0013)	(0.0015)	**(0.0009)**	(0.0012)	(0.0003)
N	401331	71631	18622	51732	42758	55037	100398	30263
White Dependent Variable = Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	-0.0009	**-0.0025**	-0.0005	-0.0005	-0.0009	-0.0005	-0.0012	-0.0006
*Offshorable	(0.0006)	**(0.0008)**	(0.0024)	(0.0009)	(0.0013)	(0.0008)	(0.0007)	(0.0002)
N	401331	71631	18622	51732	42758	55037	100398	30263
Black Dependent Variable = Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	**-0.0074**	**-0.0115**	-0.0011	-0.0018	-0.0055	-0.0071	-0.0002	0.0008
*Automatable	**(0.0020)**	**(0.0057)**	(0.0078)	(0.0042)	(0.0046)	(0.0049)	(0.0031)	(0.0035)
N	18921	2348	983	2897	854	2635	3488	3697
Black Dependent Variable = Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	**-0.0053**	**-0.0079**	-0.0047	-0.0005	-0.0022	-0.0017	0.0078	0.0009
*Offshorable	**(0.0044)**	**(0.0058)**	(0.0047)	(0.0042)	(0.0043)	(0.0031)	(0.0049)	(0.0026)
	18921	2348	983	2897	854	2635	3488	3697
Asian Dependent Variable = Probability of Being Employed in the Next Period: Automatable Analysis								
Min Wage	-0.0006	-0.0033	0.0050	-0.0002	-0.0027	-0.0020	**-0.0051**	-0.0017
*Automatable	(0.0017)	(0.0047)	(0.0067)	(0.0035)	(0.0029)	(0.0021)	**(0.0018)**	(0.0016)
N	20362	1986	1253	3917	1578	2758	4461	3413
Asian Dependent Variable Probability of Being Employed in the Next Period: Offshorable Analysis								
Min Wage	-0.0005	-0.0021	0.0000	-0.0052	-0.0055	0.0031	0.0005	-0.0007
*Offshorable	(0.0019)	(0.0053)	(0.0054)	(0.0041)	(0.0043)	(0.0025)	(0.0019)	(0.0056)
N	20362	1986	1253	3917	1578	2758	4461	3413

Table 14: Individual Level Estimates: Occupation Stayers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Probability of Being employed in the Next Period: Automatable Analysis								
Min Wage *Automatable	0.0005	**-0.0032**	0.0018	0.0005	0.0000	**-0.0039**	0.0005	0.0001
	(0.007)	**(0.0009)**	(0.0014)	(0.0015)	(0.0009)	**(0.0013)**	(0.0004)	(0.0011)
N	400613	74192	19916	58401	44903	59846	99876	35417
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage *Automatable	**-0.0018**	0.0004	-0.0012	**-0.0037**	-0.0016	**-0.0022**	-0.0015	0.0007
	(0.0009)	(0.0008)	(0.0008)	**(0.0013)**	(0.0024)	**(0.0008)**	(0.0024)	(0.000
N	239607	161006	181099	195418	24096	366721	16018	17874
Dependent Variable = Probability of Being employed in the Next Period: Offshorable Analysis								
Min Wage *Offshorable	-0.0009	-0.0017	0.0000	0.0010	0.0009	-0.0010	0.0004	-0.0000
	(0.0019)	(0.0008)	(0.0009)	(0.0004)	(0.0009)	(0.0008)	(0.0012)	(0.0003)
N	400613	74192	19916	58401	44903	59846	99876	35417
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage *Offshorable	**-0.0025**	0.0000	-0.0008	**-0.0041**	-0.0015	**-0.0021**	-0.0004	0.0005
	(0.0009)	(0.0011)	(0.0011)	**(0.0012)**	(0.0014)	**(0.0010)**	(0.0013)	(0.0011)
N	239607	161006	181099	195418	24096	366721	16018	17874

Table 15: Shares of Hours Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Automatable Hours								
Min Wage	**-0.0041**	**-0.0079**	0.0000	-0.0011	**-0.0021**	**-0.0036**	0.0029	0.0014
	(0.0008)	**(0.0016)**	(0.0014)	(0.0017)	**(0.0009)**	**(0.0014)**	(0.0018)	(0.0006)
N	4320	480	480	480	480	480	480	480
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage	**-0.0060**	0.0023	**-0.0096**	**-0.0048**	0.0010	**-0.0052**	0.0021	0.0001
	(0.0013)	(0.0016)	**(0.0034)**	**(0.0019)**	(0.0021)	**(0.0014)**	(0.0009)	(0.0020)
N	4320	4320	4320	4320	3263	4320	3612	3486
Dependent Variable = Share of Offshorable Hours								
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Min Wage	**-0.0075**	**-0.0148**	-0.0029	0.0021	-0.0009	0.0004	0.0008	-0.0014
	(0.0018)	**(0.0027)**	(0.0018)	(0.0024)	(0.0015)	(0.0010)	(0.0013)	(0.0009)
N	4320	480	480	480	480	480	480	480
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage	**-0.0097**	-0.0028	**-0.0133**	**-0.0076**	-0.0019	**-0.0082**	-0.0111	0.0047
	(0.0026)	(0.0019)	**(0.0036)**	**(0.0020)**	(0.0017)	**(0.0024)**	(0.0039)	(0.0026)
N	4320	4320	4320	4320	3263	4320	3612	3486

Table 16: Individual Level: Hours Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Difference in Hours between t and t+1: Automatable Analysis								
Min Wage *Automatable	**-0.0040**	**-0.0069**	0.0004	-0.0000	-0.0011	**-0.0075**	0.0016	0.0013
	(0.0008)	**(0.0012)**	(0.0009)	(0.0015)	(0.0007)	**(0.0019)**	(0.0019)	(0.0015)
N	427309	69105	19483	56191	43886	58664	97180	36041
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage *Automatable	**-0.0032**	-0.0010	**-0.0086**	**-0.0025**	0.0001	**-0.0036**	**-0.0058**	-0.0019
	(0.0004)	(0.0008)	**(0.0004)**	**(0.0004)**	(0.0021)	**(0.0013)**	**(0.0027)**	(0.0026)
N	228194	199115	200161	194987	32161	395002	13895	18412
Dependent Variable = Difference in Hours between t and t+1: Offshorable Analysis								
Min Wage *Offshorable	-0.0001	**-0.0038**	0.0000	0.0015	0.0003	0.0000	-0.0003	0.0009
	(0.0010)	**(0.0013)**	(0.0014)	(0.0019)	(0.0012)	(0.0009)	(0.0007)	(0.0012)
N	427309	69105	19483	56191	43886	58664	97180	36041
	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Min Wage *Offshorable	**-0.0051**	-0.0002	**-0.0065**	**-0.0081**	-0.0017	**-0.0052**	-0.0070	-0.0059
	(0.0012)	(0.0014)	**(0.0012)**	**(0.0024)**	(0.0034)	**(0.0019)**	(0.0038)	(0.0044)
N	228194	199115	200161	194987	32161	395002	13895	18412

Table 17: Dynamic Models for Shares of Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	-0.0017	-0.0046	-0.0016	0.0004	-0.0021	-0.0021	0.0045	-0.0000
	(0.0013)	(0.0028)	(0.0029)	(0.0023)	(0.0019)	(0.0024)	(0.0048)	(0.0011)
MinWage	-0.0009	0.0005	-0.0008	0.0011	-0.0010	-0.0015	-0.0023	-0.0000
Lag1	(0.0015)	(0.0024)	(0.0024)	(0.0026)	(0.0024)	(0.0023)	(0.0024)	(0.0010)
MinWage	-0.0003	-0.0018	0.0009	-0.0017	0.0000	-0.0018	-0.0012	0.0006
Lag2	(0.0017)	(0.0029)	(0.0026)	(0.0023)	(0.0019)	(0.0023)	(0.0021)	(0.0018)
N	3960	440	440	440	440	440	440	440
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Dependent Variable = Share of Offshorable Employment								
MinWage	-0.0011	-0.0034	-0.0021	-0.0000	-0.0011	-0.0000	0.0024	-0.0010
	(0.0016)	(0.0025)	(0.0022)	(0.0020)	(0.0019)	(0.0017)	(0.0043)	(0.0018)
MinWage	-0.0000	-0.0021	0.0011	0.0000	-0.0002	-0.0000	0.0011	-0.0013
Lag1	(0.0021)	(0.0027)	(0.0023)	(0.0019)	(0.0021)	(0.0021)	(0.0026)	(0.0022)
MinWage	-0.0000	0.0008	(0.0008)	-0.0005	0.0004	-0.0000	0.0000	-0.0009
Lag2	(0.0011)	(0.0029)	(0.0021)	(0.0023)	(0.0026)	(0.0024)	(0.0020)	(0.0020)
N	3960	440	440	440	440	440	440	440

Table 18: Manufacturing Low-Wage versus High-Wage Occupations- Share of Automatable analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	≥ 40 Years Old	26-39 Years Old	≤ 25 Years Old	Male	Female	White	Black	Asian
Dependent Variable = Share of Employment in Automatable Jobs									
Low-Wage									
Min Wage	**-0.0124**	**-0.0110**	**-0.0061**	-0.0031	**-0.0136**	**-0.0056**	**-0.0086**	**-0.0048**	-0.0004
	(0.0027)	**(0.0020)**	**(0.0023)**	(0.0026)	**(0.0021)**	**(0.0024)**	**(0.0021)**	**(0.0020)**	(0.0026)
N	480	480	480	421	480	480	480	390	376
High-Wage									
Min Wage	0.0023	-0.0020	0.0054	0.0002	0.0034	0.0040	0.0050	0.0016	-0.0010
	(0.0024)	(0.0027)	(0.0020)	(0.0029)	(0.0026)	(0.0028)	(0.0027)	(0.0024)	(0.0028)
N	480	480	480	400	480	480	480	396	384
Dependent Variable = Share of Employment in non-offshorable Jobs									
Low-Wage									
Min Wage	**-0.0059**	-0.0026	**-0.0093**	**-0.0066**	**-0.0058**	-0.0024	**-0.0058**	-0.0050	-0.0019
	(0.0020)	(0.0024)	**(0.0020)**	**(0.0027)**	**(0.0029)**	(0.0021)	**(0.0025)**	(0.0030)	(0.0044)
N	480	480	480	421	480	480	480	390	376
High-Wage									
Min Wage	0.0029	0.0050	-0.0010	0.0024	0.0062	-0.0014	0.0034	-0.0061	0.0015
	(0.0027)	(0.0034)	(0.0031)	(0.0035)	(0.0039)	(0.0044)	(0.0036)	(0.0045)	(0.0035)
N	480	480	480	400	480	480	480	396	384

Table 19: Manufacturing Low-Wage versus High-Wage: Individual Level Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pooled	Male	Female	>=40 years	<40 years&>25 years	<25 Years	White	Black	Asian
Dependent Variable = Probability of Being employed in the Next Period: Automatable Analysis									
Low-Wage									
Min Wage *Automatable	**-0.0090**	**-0.0035**	**-0.0055**	**-0.0111**	**-0.0099**	0.0016	**-0.0095**	**-0.0148**	0.0021
	(0.0011)	**(0.0017)**	**(0.0018)**	**(0.0024)**	**(0.0025)**	(0.0023)	**(0.0015)**	**(0.0061)**	(0.0049)
N	25981	14722	11259	12314	11412	2255	22300	2112	1569
High-Wage									
Min Wage *Automatable	0.0000	0.0005	0.0014	0.0001	0.0010	0.0009	0.0002	-0.0005	-0.0007
	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0010)	(0.0008)	(0.0021)	(0.0015)
N	23986	13457	10529	10951	11342	1693	19688	2035	2263
Dependent Variable = Probability of Being employed in the Next Period: Offshorable Analysis									
Low-Wage									
Min Wage *Offshorable	**-0.0047**	**-0.0068**	-0.0001	**-0.0061**	**-0.0034**	-0.0001	**-0.0049**	-0.0021	0.0000
	(0.0011)	**(0.0016)**	(0.0013)	**(0.0020)**	**(0.0016)**	(0.0021)	**(0.0017)**	(0.0025)	(0.0021)
N	25981	14722	11259	12314	11412	2255	22300	2112	1569
High-Wage									
Min Wage *Offshorable	-0.0009	-0.0020	0.0000	0.0006	-0.0015	-0.0008	-0.0011	0.0000	-0.0014
	(0.0012)	(0.0014)	(0.0017)	(0.0021)	(0.0019)	(0.0017)	(0.0013)	(0.0011)	(0.0020)
N	23986	13457	10529	10951	11342	1693	19688	2035	2263

Table 20: Future Automations of Selected Low-skilled Occupations

Occupation	Comments
Hairdresser	Very few patents have been filed that directly substitute for the work done by a hairdresser[33]. This is intuitive given that hairdressing involved interpersonal engagement that is unpredictable, as well as a set of tasks that are not completed in any specific sequence. No technology has been piloted successfully as a substitute for a hairdressing, or a proportion of their tasks to our knowledge.
Shelf Stacker/Picker	There have been many patents filed for robots that would substitute directly for shelf stackers and pickers. Robots are now able to pick things up and move them to another area, however more innovation is needed in machine learning whereby the computer is trained to understand context and pick items of different sizes. Amazon is a notable example of a company already using shelf stacking robots as part of their fulfillment process, and investing heavily in trying to create a robot with enough human dexterity to be a picker. Currently these robots move merchandise around the warehouse and work in complement with the remaining low wage pickers.
Childcare	With the exception of a few patents for smart home robots that can monitor and interact with children, R&D is low. No technology has been piloted successfully as a substitute for a child carer, or a proportion of their tasks to our knowledge.
Supermarket Cashiers	Already most supermarkets in the UK are fitted with automated teller machines. These have been available for some time, however patent activity on Google Patents is low on innovation that goes beyond what we already have in stores now in the last couple of years. Most of the filed patents aim to improve on this technology. This suggests that the number of cashier jobs may fall, but at a slow rate, as customers become more familiar with the current systems. However, cashiers will still be needed in the medium term for people who do not want to self check-out, and to troubleshoot when self check-out fails.
Waiter	In the last decade, there has been a rise in the numbers of patents filled for waiter robots. The proposed systems are as yet not very sophisticated. For example, a new robot system relies on the robot having a designated path with positioning intervals that are arranged to correspond to tables. This relies on customers removing their food personally. Nevertheless, many of the patents mention cutting down on workers and cost efficiencies, and R&D is busy in this area. Additionally, there is evidence of establishments where these technologies have already been launched. For example, the fore mentioned system has had some adoptions in China, with some reports of success (but other reports of failure).

[33] The main innovation in this area is with a hair-washing robot, with a small number of patents filed, the first in 2009. However, there have been no successful trials of this technology in business as yet.

Bar Tender	There are many patents currently filed for bar tending technology. Notably, right now, this works best when menus are limited and ingredients come in containers that are the same size and shape. Successful examples of bar tending robots are becoming more common and include, Café X in San Francisco who has adopted a large robotic arm as their barista and Robots Bar in Ilmenau who has employed humanoid Carl to mix drinks. The innovations that have been successful involve customers ordering drinks from an iPad, so a staff member is required to liaise with customers and show them how to interact with their bar tender bot.
Driver (taxi, delivery etc).	This is the job that has had the most innovation for replacements with respect to sheer number of patents filed, since 2015 the numbers have rose exponentially. 2015 was also the year that Google completed its first driverless journey. Domino's Pizza is still rolling out 'DRU' – an autonomous delivery vehicle which cruises along pavements to bring pizza to its customers. In June 2017 Ocado was the first UK company to trial driverless deliveries. Currently, under UK law a driver is still required to be present in the car, however assuming that laws keep pace with technology the success of robots so far in this area, along with the quantity of R&D going on suggests that there will be a sharp decrease in the number of driver jobs over the next decade.
Cleaner	There are many patents filed under the heading of 'robot cleaner.' However, all of these are still really just household equipment, more advanced than the hoover, rather than a replacement for a domestic cleaner. Examples include floor washing robots and a robot that irons shirts. These innovations may raise the productivity of a domestic cleaner but are not direct substitutes. There is currently no patent filed on Google patents that is anywhere near a substitute.
Security Guard	Improvements of the current security robots on offer are evident from the latest patents filed on Google Patents. Overall, the current offerings rely on a robot doing rounds in a fixed schedule, with the ability to flag up unusual occurrences such as intruders. This ability comes from sensors. These systems currently rely on a human monitor who can react to any alarm that they raise, and monitor the live stream feed that is uploaded to a server. However, there are many less monitors as compared with security guards. The most successful security robot comes from Knightscope, who this year raised $15 million in a mini-IPO. Their robot is currently employed successfully in various roles (mall, street and company) in the US.
Brick Layer	There are various patents filed whose aim is to lay bricks. However, the most recent patents still rely on their being a pre-determined positioning for the bricks to be laid and/or a mason to work alongside the robot. The most successful robot so far is SAM created by construction robotics, with claims of laying 3000 bricks per day. Hadrian X a competitor claims to lay 1000 bricks per hour and currently has a memorandum of understanding with Caterpillar construction.

Appendix A: US Definitions of Automation and Offshorable Employment:

Table A.1: Full Sample Estimates 1994 – 2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0041**	**-0.0071**	0.0004	-0.0004	0.0013	**-0.0038**	0.0016	0.0007
	(0.0013)	**(0.0025)**	(0.0024)	(0.0024)	(0.0024)	**(0.0020)**	(0.0025)	(0.0021)
N	4320	480	480	480	480	480	480	480
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0023	**-0.0065**	-0.0019	-0.0019	-0.0009	-0.0030	-0.0004	-0.0026
	(0.0015)	**(0.0031)**	(0.0025)	(0.0026)	(0.0023)	(0.0025)	(0.0023)	(0.0022)
N	4320	480	480	480	480	480	480	480

Notes: OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who have a GCSE equivalent or less and work in an occupation that is in the lowest quantile of the income distribution. The definition of automatable and offshorable employment are provided in Autor and Dorn (2013), Autor Dorn and Hanson (2015), Firpo, Fortin, and Lemieux (2011) and Autor and Dorn (2013) respectively. A job is classified as automatable or offshorable at the three-digit occupation code level. The share of employment is calculated by industry, state, and year. All regressions include area fixed effects and area specific time trends. Regressions also include: Area level demographics that vary over time: average age, education, gender; Occupation demographics measured at the area/industry/year level: average age, education, gender. The pooled regression also has industry fixed effects. The minimum wage is measured in 2015 prices.

Table A.2: US Full Sample Estimates 1994 – 2017 by Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Males								
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0053**	**-0.0102**	0.0003	-0.0009	-0.0016	**-0.0049**	-0.0010	-0.0004
	(0.0014)	**(0.0029)**	(0.0022)	(0.0028)	(0.0022)	**(0.0025)**	(0.0025)	(0.0022)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0039**	**-0.0071**	0.0017	-0.0001	-0.0008	**-0.0053**	-0.0027	0.0010
	(0.0016)	**(0.0029)**	(0.0025)	(0.0027)	(0.0026)	**(0.0024)**	(0.0020)	(0.0029)
N	4320	480	480	480	480	480	480	480
Females								
Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0022	**-0.0052**	-0.0002	-0.0030	-0.0003	-0.0008	-0.0014	-0.0007
	(0.0015)	**(0.0021)**	(0.0022)	(0.0025)	(0.0023)	(0.0024)	(0.0017)	(0.0005)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0012	-0.0027	-0.0009	-0.0009	-0.0008	0.0007	0.0010	-0.0007
	(0.0018)	(0.0020)	(0.0023)	(0.0020)	(0.0025)	(0.0025)	(0.0023)	(0.0022)
N	4320	480	480	480	480	480	480	480

Table A.3: Full Sample Estimates 1994 – 2017 by age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
>= 40 Years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0091**	**-0.0135**	0.0000	-0.0005	-0.0008	-0.0012	-0.0005	-0.0018
	(0.0013)	**(0.0026)**	(0.0022)	(0.0022)	(0.0022)	(0.0029)	(0.0025)	(0.0025)
N	4320	480	480	480	480	480	480	480
>= 40 Years Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0044**	**-0.0078**	-0.0005	-0.0010	-0.0022	-0.0023	0.0022	0.0019
	(0.0015)	**(0.0021)**	(0.0024)	(0.0021)	(0.0024)	(0.0024)	(0.0027)	(0.0029)
N	4320	480	480	480	480	480	480	480
>=26 years and <=39 years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0047**	**-0.0054**	0.0012	-0.0002	-0.0003	**-0.0055**	-0.0007	0.0014
	(0.0013)	**(0.0024)**	(0.0028)	(0.0021)	(0.0021)	**(0.0020)**	(0.0028)	(0.0024)
N	4320	480	480	480	480	480	480	480
>=26 years and <=39 years Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0030**	**-0.0062**	-0.0004	-0.0006	0.0013	-0.0010	-0.0004	-0.0012
	(0.0014)	**(0.0028)**	(0.0021)	(0.0020)	(0.0023)	(0.0023)	(0.0023)	(0.0027)
N	4320	480	480	480	480	480	480	480
<25 years Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0020	-0.0007	0.0001	0.0001	-0.0003	**-0.0043**	-0.0022	-0.0006
	(0.0019)	(0.0025)	(0.0028)	(0.0025)	(0.0024)	**(0.0022)**	(0.0022)	(0.0023)
N	3263	426	383	431	383	442	443	427
<25 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	0.0011	0.0009	0.0000	-0.0003	**-0.0039**	0.0000	0.0002
	(0.0017)	(0.0022)	(0.0023)	(0.0021)	(0.0024)	**(0.0020)**	(0.0020)	(0.0026)
N	3263	426	383	431	383	442	443	427

Table A.4: Full Sample Estimates 1994 – 2017 by race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
White Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0041**	**-0.0094**	0.0001	0.0019	-0.0001	-0.0016	0.0033	-0.0006
	(0.0014)	**(0.0026)**	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0026)	(0.0027)
N	4320	480	480	480	480	480	480	480
White Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0027**	**-0.0078**	-0.0035	0.0001	-0.0007	-0.0020	-0.0004	-0.0012
	(0.0013)	**(0.0020)**	(0.0022)	(0.0021)	(0.0023)	(0.0021)	(0.0023)	(0.0027)
N	4320	480	480	480	480	480	480	480
Black Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0075**	**-0.0091**	0.0001	-0.0038	-0.0004	0.0000	0.0014	-0.0025
	(0.0018)	**(0.0025)**	(0.0024)	(0.0029)	(0.0023)	(0.0027)	(0.0021)	(0.0024)
N	3612	452	440	451	445	455	459	443
Black Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0023	-0.0051	0.0015	-0.0042	-0.0026	0.0005	0.0000	-0.0018
	(0.0016)	(0.0028)	(0.0021)	(0.0028)	(0.0028)	(0.0028)	(0.0023)	(0.0027)
N	3612	452	440	451	445	455	459	443
Asian Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0013	-0.0031	0.0006	-0.0051	-0.0070	-0.0111	0.0017	-0.0140
	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0023)	(0.0022)	(0.0029)	(0.0029)
N	3486	370	396	358	369	383	390	410
Asian Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0021	-0.0014	0.0015	-0.0025	-0.0032	**-0.0050**	0.0009	-0.0031
	(0.0025)	(0.0022)	(0.0026)	(0.0027)	(0.0029)	**(0.0024)**	(0.0025)	(0.0025)
N	3486	370	396	358	369	383	390	410

Appendix B: 0.25 Replication
Table B.1: Full Sample Estimates 1994 – 2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0055**	**-0.0089**	-0.0021	-0.0027	-0.0029	**-0.0028**	-0.0014	-0.0011
	(0.0009)	**(0.0014)**	(0.0015)	(0.0016)	(0.0019)	**(0.0014)**	(0.0013)	(0.0015)
N	4320	480	480	480	480	480	480	480
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0021**	**-0.0043**	-0.0010	-0.0014	-0.0000	-0.0007	0.0009	-0.0000
	(0.0012)	**(0.0014)**	(0.0013)	(0.0019)	(0.0007)	(0.0004)	(0.0033)	(0.0005)
N	4320	480	480	480	480	480	480	480

Table B.2: Full Sample Estimates 1994 – 2017 by Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Males								
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0053**	**-0.0113**	-0.0001	-0.0018	0.0024	-0.0021	-0.0000	-0.0010
	(0.0011)	**(0.0014)**	(0.0014)	(0.0014)	(0.0016)	(0.0013)	(0.0011)	(0.0015)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0029**	**-0.0055**	0.0031	-0.0007	0.0002	-0.0011	-0.0049	-0.0004
	(0.0008)	**(0.0019)**	(0.0024)	(0.0011)	(0.0003)	(0.0008)	(0.0023)	(0.0003)
N	4320	480	480	480	480	480	480	480
Females								
Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0016	-0.0019	-0.0010	-0.0019	0.0002	**-0.0027**	**-0.0023**	-0.0007
	(0.0009)	(0.0016)	(0.0016)	(0.0017)	(0.0018)	**(0.0013)**	**(0.0011)**	(0.0018)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	-0.0012	-0.0000	-0.0021	-0.0000	-0.0024	-0.0021	-0.0015
	(0.0007)	(0.0017)	(0.0015)	(0.0015)	(0.0017)	(0.0018)	(0.0012)	(0.0016)
N	4320	480	480	480	480	480	480	480

Table B.3: Full Sample Estimates 1994 – 2017 by Age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
>= 40 Years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0066**	**-0.0097**	0.0015	-0.0014	**-0.0019**	0.0010	**-0.0033**	-0.0021
	(0.0006)	**(0.0018)**	(0.0014)	(0.0019)	**(0.0010)**	(0.0014)	**(0.0014)**	(0.0012)
N	4320	480	480	480	480	480	480	480
>= 40 Years Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0039**	**-0.0072**	0.0004	-0.0009	-0.0000	-0.0007	-0.0029	-0.0001
	(0.0007)	**(0.0018)**	(0.0006)	(0.0009)	(0.0001)	(0.0013)	(0.0019)	(0.0007)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0050**	**-0.0061**	-0.0014	-0.0019	-0.0018	**-0.0047**	-0.0031	-0.0000
	(0.0009)	**(0.0017)**	(0.0011)	(0.0015)	(0.0013)	**(0.0020)**	(0.0019)	(0.0005)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0019	-0.0031	-0.0000	-0.0019	0.0004	-0.0000	0.0009	-0.0011
	(0.0010)	(0.0017)	(0.0011)	(0.0019)	(0.0017)	(0.0012)	(0.0013)	(0.0019)
N	4320	480	480	480	480	480	480	480
<25 years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0017**	-0.0018	0.0001	0.0000	0.0001	-0.0027	-0.0023	-0.0004
	(0.0008)	(0.0015)	(0.0001)	(0.0003)	(0.0004)	(0.0018)	(0.0017)	(0.0003)
N	3263	426	383	431	383	442	443	427
<25 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	0.0000	0.0000	0.0000	-0.0004	-0.0007	-0.0015	-0.0001
	(0.0007)	(0.0014)	(0.0010)	(0.0011)	(0.0010)	(0.0014)	(0.0012)	(0.0012)

Table B.4: Full Sample Estimates 1994 – 2017 by race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
White Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0032**	**-0.0085**	-0.0019	0.0003	-0.0016	-0.0018	-0.0019	-0.0000
	(0.0010)	**(0.0017)**	(0.0018)	(0.0014)	(0.0016)	(0.0013)	(0.0012)	(0.0010)
N	4320	480	480	480	480	480	480	480
White Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0021**	**-0.0060**	-0.0017	-0.0000	-0.0008	-0.0017	-0.0019	-0.0000
	(0.0008)	**(0.0012)**	(0.0014)	(0.0010)	(0.0014)	(0.0017)	(0.0020)	(0.0001)
N	4320	480	480	480	480	480	480	480
Black Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0083**	**-0.0129**	-0.0000	0.0008	-0.0006	-0.0008	-0.0016	0.0002
	(0.0019)	**(0.0029)**	(0.0014)	(0.0015)	(0.0018)	(0.0017)	(0.0018)	(0.0011)
N	3612	452	440	451	445	455	459	443
Black Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0015	-0.0022	-0.0030	0.0001	0.0017	0.0000	0.0019	0.0005
	(0.0021)	(0.0023)	(0.0018)	(0.0019)	(0.0020)	(0.0016)	(0.0018)	(0.0005)
N	3612	452	440	451	445	455	459	443
Asian Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0016	-0.0030	0.0000	-0.0000	-0.0004	**-0.0059**	-0.0008	**-0.0046**
	(0.0018)	(0.0030)	(0.0029)	(0.0028)	(0.0027)	**(0.0026)**	(0.0028)	**(0.0025)**
N	3486	370	396	358	369	383	390	410
Asian Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	-0.0018	0.0000	-0.0040	-0.0000	0.0029	0.0000	0.0000
	(0.0034)	(0.0038)	(0.0036)	(0.0038)	(0.0031)	(0.0032)	(0.0038)	(0.0031)
N	3486	370	396	358	369	383	390	410

0.40 Replication

Table B.5: Full Sample Estimates 1994 – 2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0019**	**-0.0030**	-0.0019	-0.0017	-0.0017	-0.0018	0.0010	-0.0009
	(0.0009)	**(0.0012)**	(0.0012)	(0.0018)	(0.0015)	(0.0012)	(0.0018)	(0.0014)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0004	-0.0023	-0.0004	-0.0008	-0.0015	0.0000	0.0023	0.0000
	(0.0003)	(0.0019)	(0.0014)	(0.0016)	(0.0013)	(0.0014)	(0.0015)	(0.0014)
N	4320	480	480	480	480	480	480	480

Table B6: Full Sample Estimates 1994 – 2017 by Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Males								
Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0020**	**-0.0058**	-0.0000	-0.0013	0.0000	-0.0028	-0.0016	-0.0000
	(0.0009)	**(0.0019)**	(0.0011)	(0.0015)	(0.0013)	(0.0010)	(0.0019)	(0.0016)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	**-0.0015**	**-0.0036**	-0.0010	-0.0000	0.0000	-0.0002	-0.0017	-0.0000
	(0.0009)	**(0.0017)**	(0.0019)	(0.0014)	(0.0015)	(0.0014)	(0.0018)	(0.0012)
N	4320	480	480	480	480	480	480	480
Females								
Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0000	-0.0020	-0.0000	-0.0018	0.0000	-0.0024	-0.0020	-0.0000
	(0.0009)	(0.0015)	(0.0017)	(0.0015)	(0.0012)	(0.0015)	(0.0019)	(0.0014)
N	4320	480	480	480	480	480	480	480
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0014	-0.0013	0.0000	-0.0030	0.0000	-0.0027	-0.0000	-0.0011
	(0.0009)	(0.0019)	(0.0017)	(0.0019)	(0.0018)	(0.0015)	(0.0014)	(0.0013)
N	4320	480	480	480	480	480	480	480

Table B7: Full Sample Estimates 1994 – 2017 by Age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking & Finance	P Adm Educ and Health	Other Services
>= 40 Years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0046**	**-0.0078**	-0.0000	-0.0005	-0.0015	0.0001	-0.0014	-0.0007
	(0.0009)	**(0.0016)**	(0.0015)	(0.0010)	(0.0018)	(0.0015)	(0.0019)	(0.0018)
N	4320	480	480	480	480	480	480	480
>= 40 Years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0015	**-0.0045**	0.0000	-0.0000	-0.0003	-0.0005	-0.0020	0.0000
	(0.0010)	**(0.0016)**	(0.0013)	(0.0011)	(0.0018)	(0.0018)	(0.0018)	(0.0016)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0029**	**-0.0030**	-0.0004	-0.0019	-0.0000	**-0.0039**	-0.0006	-0.0000
	(0.0011)	**(0.0014)**	(0.0016)	(0.0014)	(0.0012)	**(0.0013)**	(0.0015)	(0.0000)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0012	**-0.0022**	0.0004	-0.0009	0.0021	0.0000	-0.0020	-0.0020
	(0.0009)	**(0.0010)**	(0.0014)	(0.0016)	(0.0016)	(0.0010)	(0.0014)	(0.0027)
N	4320	480	480	480	480	480	480	480
<25 years Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0000	-0.0010	0.0000	0.0000	0.0011	0.0027	-0.0019	-0.0000
	(0.0009)	(0.0011)	(0.0010)	(0.0017)	(0.0011)	(0.0018)	(0.0016)	(0.0018)
N	3263	426	383	431	383	442	443	427
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0000	0.0009	-0.0000	0.0002	-0.0005	-0.0016	-0.0015	-0.0000
	(0.0009)	(0.0010)	(0.0016)	(0.0012)	(0.0012)	(0.0015)	(0.0016)	(0.0003)
N	3263	426	383	431	383	442	443	427

\

Table B8: Full Sample Estimates 1994 – 2017 by Race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
White Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0020**	**-0.0053**	-0.0008	-0.0014	-0.0009	-0.0021	0.0012	0.0000
	(0.0009)	**(0.0020)**	(0.0019)	(0.0012)	(0.0019)	(0.0019)	(0.0018)	(0.0004)
N	**4320**	**480**	480	480	480	480	480	480
White Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0011	-0.0029	-0.0016	0.0003	0.0012	0.0000	-0.0021	-0.0009
	(0.0010)	(0.0017)	(0.0018)	(0.0017)	(0.0018)	(0.0010)	(0.0016)	(0.0014)
N	4320	480	480	480	480	480	480	480
Black Dependent Variable = Share of Automatable Employment								
Min Wage	**-0.0034**	**-0.0060**	0.0000	0.0011	**-0.0023**	-0.0006	-0.0001	0.0000
	(0.0010)	**(0.0012)**	(0.0012)	(0.0017)	**(0.0011)**	(0.0017)	(0.0012)	(0.0001)
N	3612	452	440	451	445	455	459	443
Black Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0023	-0.0020	-0.0007	0.0014	-0.0015	-0.0004	0.0018	-0.0030
	(0.0019)	(0.0029)	(0.0026)	(0.0022)	(0.0024)	(0.0026)	(0.0025)	(0.0022)
N	3612	452	440	451	445	455	459	443
Asian Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0019	-0.0014	0.0000	0.0000	-0.0018	-0.0036	-0.0016	-0.0007
	(0.0017)	(0.0024)	(0.0031)	(0.0030)	(0.0034)	(0.0029)	(0.0029)	(0.0008)
N	3486	370	396	358	369	383	390	410
Asian Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0004	-0.0009	0.0000	-0.0019	0.0000	-0.0033	0.0000	0.0000
	(0.0033)	(0.0027)	(0.0030)	(0.0035)	(0.0031)	(0.0034)	(0.0038)	(0.0039)
N	3486	370	396	358	369	383	390	410

Appendix C: Effects on the Highest Skilled Group
Table C.1: Pooled Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Automatable Employment								
Min Wage	0.0000	0.0003	0.0000	-0.0012	0.0001	-0.0000	0.0020	0.0000
	(0.0008)	(0.0019)	(0.0011)	(0.0018)	(0.0015)	(0.0012)	(0.0013)	(0.0012)
N	4320	480	480	480	480	480	480	480
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	Public Admin Education and Health	Other Services
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0001	0.0006	-0.0014	-0.0000	0.0000	0.0019	0.0013	0.0000
	(0.0010)	(0.0019)	(0.0016)	(0.0010)	(0.0011)	(0.0014)	(0.0016)	(0.0011)
N	4320	480	480	480	480	480	480	480

Table C.2: Gender Specific Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
Males								
Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0002	-0.0000	0.0000	-0.0004	0.0005	-0.0000	-0.0002	0.0018
	(0.0009)	(0.0012)	(0.0016)	(0.0010)	(0.0015)	(0.0011)	(0.0014)	(0.0012)
N	4119	460	460	460	460	460	460	460
Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0000	0.0026	-0.0003	0.0000	0.0000	-0.0002	-0.0000	-0.0000
	(0.0007)	(0.0017)	(0.0019)	(0.0018)	(0.0012)	(0.0013)	(0.0019)	(0.0018)
N	4119	460	460	460	460	460	460	460
Females								
Dependent Variable = Share of Automatable Employment								
Min Wage	0.0009	-0.0003	0.0000	0.0007	0.0000	-0.0004	-0.0001	0.0000
	(0.0008)	(0.0014)	(0.0011)	(0.0014)	(0.0012)	(0.0012)	(0.0019)	(0.0012)
N	4119	460	460	460	460	460	460	460
Dependent Variable = Share of Offshorable Employment								
Min Wage	0.0004	0.0000	0.0018	0.0001	-0.0001	-0.0009	-0.0000	-0.0001
	(0.0011)	(0.0013)	(0.0010)	(0.0016)	(0.0017)	(0.0015)	(0.0012)	(0.0011)
N	4119	460	460	460	460	460	460	460

Table C.3: Age Specific Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
>= 40 Years Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0005	0.0001	0.0000	-0.0000	-0.0003	-0.0001	-0.0001	-0.0000
	(0.0003)	(0.0002)	(0.0011)	(0.0000)	(0.0002)	(0.0002)	(0.0012)	(0.0006)
N	4320	480	480	480	480	480	480	480
>= 40 Years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0004	0.0013	0.0000	0.0000	0.0001	0.0000	0.0017	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0012)	(0.0019)	(0.0005)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Automatable Employment								
Min Wage	0.0000	0.0009	0.0001	0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0005)	(0.0010)	(0.0003)	(0.0000)	(0.0002)	(0.0000)	(0.0004)	(0.0006)
N	4320	480	480	480	480	480	480	480
>25 years and <40 years Dependent Variable = Share of Offshorable Employment								
Min Wage	-0.0000	0.0000	0.0000	0.0001	0.0004	0.0003	0.0000	0.0000
	(0.0014)	(0.0003)	(0.0004)	(0.0000)	(0.0012)	(0.0000)	(0.0009)	(0.0014)
N	4320	480	480	480	480	480	480	480
<25 years Dependent Variable = Share of Automatable Employment								
Min Wage	-0.0000	-0.0003	0.0002	0.0013	0.0000	0.0000	-0.0009	0.0001
	(0.0010)	(0.0011)	(0.0011)	(0.0018)	(0.0012)	(0.0011)	(0.0014)	(0.0013)
N	3118	399	390	414	396	419	420	438
<25 years Dependent Variable = Share of Offshorable Employment								
Min Wage	0.0004	-0.0002	-0.0000	-0.0000	-0.0009	-0.0006	-0.0001	-0.0011
	(0.0008)	(0.0010)	(0.0013)	(0.0014)	(0.0014)	(0.0013)	(0.0011)	(0.0014)
N	3118	399	390	414	396	419	420	438

Table C.4: Race specific estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Admin Educ and Health	Other Services
White Dependent Variable = Share of Automatable Employment								
Min Wage	0.0004	0.0002	0.0000	0.0000	-0.0000	0.0001	0.0003	0.0000
	(0.0003)	(0.0008)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0004)	(0.0004)
N	4320	480	480	480	480	480	480	480
White Dependent Variable = Share of Offshorable Employment								
Min Wage	0.0000	-0.0000	-0.0000	0.0001	0.0002	0.0003	-0.0001	-0.0000
	(0.0004)	(0.0000)	(0.0003)	(0.0001)	(0.0005)	(0.0004)	(0.0004)	(0.0002)
N	4320	480	480	480	480	480	480	480
Black Dependent Variable = Share of Automatable Employment								
Min Wage	0.0007	0.0001	0.0001	0.0002	0.0005	0.0006	0.0013	0.0001
	(0.0008)	(0.0002)	(0.0002)	(0.0004)	(0.0012)	(0.0005)	(0.0009)	(0.0004)
N	3184	430	418	454	452	426	437	446
Black Dependent Variable = Share of Offshorable Employment								
Min Wage	0.0003	0.0014	-0.0007	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0009)	(0.0012)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0003)	(0.0002)
N	3184	430	418	454	452	426	437	446
Asian Dependent Variable = Share of Automatable Employment								
Min Wage	0.0018	0.0020	0.0007	0.0010	0.0003	-0.0011	0.0002	0.0000
	(0.0016)	(0.0023)	(0.0023)	(0.0021)	(0.0019)	(0.0028)	(0.0027)	(0.0020)
N	2860	356	370	380	391	410	392	398
Asian Dependent Variable = Share of Offshorable Employment								
Min Wage	0.0000	0.0000	0.0000	-0.0008	0.0020	0.0003	0.0000	0.0002
	(0.0013)	(0.0025)	(0.0029)	(0.0018)	(0.0021)	(0.0024)	(0.0028)	(0.0019)

N	2860	356	370	380	391	410	392	398

Appendix D: Including Immigrants in the Shares of Employment Analysis
Table D.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0022**	**-0.0059**	-0.0009	-0.0010	-0.0019	**-0.0025**	0.0003	-0.0001
	(0.0008)	**(0.0012)**	(0.0010)	(0.0021)	(0.0019)	**(0.0013)**	(0.0016)	(0.0013)
N	**4320**	**480**	480	480	480	**480**	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
Minwage	**-0.0037**	-0.0014	**-0.0051**	**-0.0042**	0.0010	**-0.0022**	**-0.0069**	-0.0027
	(0.0010)	(0.0010)	**(0.0010)**	**(0.0008)**	(0.0011)	**(0.0010)**	**(0.0020)**	(0.0017)
N	4320	4320	4320	4320	3263	4320	3914	4002
Dependent Variable = Share of Offshorable Employment								
MinWage	-0.0017	-0.0029	0.0004	-0.0010	-0.0019	0.0000	0.0016	0.0000
	(0.0008)	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0008)	(0.0015)	(0.0014)
N	4320	480	480	480	480	480	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
MinWage	-0.0020	-0.0000	-0.0018	-0.0018	-0.0010	-0.0021	-0.0020	-0.0011
	(0.0007)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0011)	(0.0013)	(0.0020)
N	4320	4320	4320	4320	3263	4320	3914	4002

Appendix E: Changing how the minimum wage is defined in the Shares of Employment Analysis

Table E.1 Measured using the current year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0022**	**-0.0059**	-0.0009	-0.0010	-0.0019	**-0.0025**	0.0003	-0.0001
	(0.0008)	**(0.0012)**	(0.0010)	(0.0021)	(0.0019)	**(0.0013)**	(0.0016)	(0.0013)
N	**4320**	**480**	480	480	480	**480**	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
Minwage	**-0.0037**	-0.0014	**-0.0051**	**-0.0042**	0.0010	**-0.0022**	**-0.0069**	-0.0027
	(0.0010)	(0.0010)	**(0.0010)**	**(0.0008)**	(0.0011)	**(0.0010)**	**(0.0020)**	(0.0017)
N	4320	4320	4320	4320	3263	4320	3914	4002
Dependent Variable = Share of Offshorable Employment								
MinWage	-0.0017	-0.0029	0.0004	-0.0010	-0.0019	0.0000	0.0016	0.0000
	(0.0008)	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0008)	(0.0015)	(0.0014)
N	4320	480	480	480	480	480	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
MinWage	-0.0020	-0.0000	-0.0018	-0.0018	-0.0010	-0.0021	-0.0020	-0.0011
	(0.0007)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0011)	(0.0013)	(0.0020)
N	4320	4320	4320	4320	3263	4320	3914	4002

Table E.1 Measured using the current year minimum wage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0014**	**-0.0037**	-0.0004	-0.0012	-0.0011	-0.0013	0.0000	0.0002
	(0.0007)	**(0.0011)**	(0.0011)	(0.0020)	(0.0019)	(0.0012)	(0.0013)	(0.0014)
N	**4320**	**480**	480	480	480	**480**	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
Minwage	**-0.0022**	-0.0006	**-0.0040**	**-0.0021**	-0.0007	**-0.0022**	**-0.0069**	-0.0027
	(0.0011)	(0.0010)	**(0.0011)**	**(0.0010)**	(0.0014)	**(0.0010)**	**(0.0020)**	(0.0017)
N	4320	4320	4320	4320	3263	4320	3612	3486
Dependent Variable = Share of Offshorable Employment								
MinWage	-0.0008	-0.0018	0.0000	0.0008	0.0004	0.0000	0.0016	0.0009
	(0.0010)	(0.0014)	(0.0015)	(0.0009)	(0.0011)	(0.0018)	(0.0014)	(0.0012)
N	4320	480	480	480	480	480	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
MinWage	-0.0021	0.0004	-0.0014	-0.0005	-0.0011	-0.0010	-0.0016	-0.0000
	(0.0006)	(0.0009)	(0.0010)	(0.0005)	(0.0008)	(0.0012)	(0.0014)	(0.0021)
N	4320	4320	4320	4320	3263	4320	3612	3486

\

Table E.2 Measured using the one-year lag minimum wage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled	Manufacturing	Construction	Hotels and Restaurants	Transport and Communication	Banking and Finance	P Adm Educ and Health	Other Services
Dependent Variable = Share of Automatable Employment								
MinWage	**-0.0028**	**-0.0069**	-0.0014	-0.0022	-0.0013	**-0.0030**	-0.0009	-0.0002
	(0.0007)	**(0.0012)**	(0.0013)	(0.0018)	(0.0017)	**(0.0014)**	(0.0012)	(0.0010)
N	**4320**	**480**	480	480	480	480	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
Minwage	**-0.0038**	-0.0010	**-0.0057**	**-0.0050**	-0.0017	**-0.0031**	**-0.0059**	**-0.0035**
	(0.0010)	(0.0009)	**(0.0010)**	**(0.0013)**	(0.0013)	**(0.0012)**	**(0.0028)**	**(0.0018)**
N	4320	4320	4320	4320	3263	4320	3612	3486
Dependent Variable = Share of Offshorable Employment								
MinWage	**-0.0022**	**-0.0048**	0.0008	0.0011	-0.0012	-0.0010	-0.0015	-0.0000
	(0.0008)	**(0.0015)**	(0.0013)	(0.0010)	(0.0010)	(0.0016)	(0.0013)	(0.0001)
N	4320	480	480	480	480	480	480	480
	Males	Females	>=40 Years	>25 years and <40 years	<25 Years	White	Black	Asian
MinWage	**-0.0046**	-0.0011	**-0.0029**	-0.0015	**-0.0019**	**-0.0020**	-0.0021	-0.0010
	(0.0010)	(0.0010)	**(0.0012)**	(0.0008)	**(0.0010)**	**(0.0011)**	(0.0013)	(0.0020)
N	4320	4320	4320	4320	3263	4320	3612	3486

Appendix F: ASHE Minimum Wage Ratio Re Analysis
Table F.1: ASHE replication for Low Paid Workers: Share of employment analysis by Strata

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	>=40 years	<40 years and >25 years	<25 years	Male	Female
Min Wage *Automatable	-0.0970	-0.0565	-0.0874	-0.0342	-0.0931	-0.0898
	(0.0754)	(0.0565)	(0.0815)	(0.0347)	(0.0376)	(0.0813)
N	2036	2036	2036	2036	2036	2036
	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	>=40 years	<40 years and >25 years	<25 years	Male	Female
Min Wage* Offshorable	**-0.0391**	0.0048	**-0.0318**	**-0.0431**	**-0.0357**	-0.0132
	(0.0141)	(0.0108)	**(0.0159)**	**(0.0140)**	**(0.0125)**	(0.0105)
N	2036	2036	2036	2036	2036	2036

Notes: Data are from the 1998- 2015 ASHE surveys. OLS coefficient estimates are reported, with standard errors in parentheses. Standard errors are robust to unknown heteroscedasticity. Low-skilled workers are defined as those who are in the bottom 20% of the income distribution in any given year. A person is defined as a minimum wage worker if they were paid below the minimum wage one year before an increase. The definition of automatable employment is created from variables in the UK Skills and Employment Surveys Series Dataset. A job is classified as automatable at the three-digit occupation code level. The share of automatable employment is calculated by industry, state, and year. The share of offshorable employment is calculated in the same manner. All regressions include area fixed effects and area specific time trends. The pooled regression also has industry fixed effects. The minimum wage ratio is defined as the proportion of low paid workers that are affected by minimum wage increases.