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Abstract

Drawing on 28 million observations on people's running times in a free weekly 5 kilometre running event, Parkrun, we examine whether labour market conditions affect fitness. Running times improve during recessions for men and women aged 50 and above but worsen for men aged 20-49 and women aged 20-29, suggesting that the fall in the opportunity costs of fitness during recessions is the dominant factor for elderly runners, whereas the income effect induced by unemployment dominates for prime age workers. Participation in Parkrun is not sensitive to the business cycle so our results are not driven by compositional changes.

JEL Classification: I12; I30
Key words: fitness; health; business cycle; Parkrun

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1. Introduction

There is conflicting evidence in the literature regarding the effect the business cycle has on individuals' health. One of the earliest studies found state-level mortality rates in the United States were strongly pro-cyclical (Ruhm 2020) whereas person-level studies find people experience worse health after becoming unemployed (Banks et al. 2020). The literature indicates that aggregation biases may be important in explaining disparate results, but results may also vary because a number of potentially countervailing mechanisms link business cycle effects to health and, in many studies, these are not directly observed. On the one hand, the falling demand for labour accompanying a recession will increase unemployment and reduce hours for those remaining in work. This means fewer people are commuting for work and have more time available to lead a healthy lifestyle – for instance through increased exercise or cooking healthy meals. On the other hand, job loss, reduced working hours and downward adjustments to nominal hourly wages can reduce income so that people struggle to buy high-quality food or attend sports facilities.

There are also methodological and data shortcomings to existing studies which may obscure heterogeneous effects of the business cycle across people and health conditions. Reflecting on this when reviewing the country-level studies Drydakis (2016) concluded that "as the impact of recessions could well differ between subgroups within a country, more work is needed on this issue, as many studies have failed to control for age cohorts, pre-recession health conditions, and low-income groups".

We contribute to the literature by focusing specifically on the fitness levels of individuals who participate in Parkrun (www.parkrun.org.uk). Parkruns are free weekly 5 kilometre running events held around the world, although we restrict our attention to events in the United Kingdom. Using 28 million observations on almost 2 million so-called Parkrunners between 2004 and 2020, we examine whether fitness levels, as indicated by running times, are affected by the business cycle. Our individual-level data allow us to track when and where individuals run over time so we can establish patterns of participation and, when they do run, changes in running times. We map in local labour market conditions in the areas people run in, capturing variance in those conditions by age and gender to identify heterogeneity in business cycle conditions across different demographic groups. Although the labour market status of runners is unknown to us, we assume that changes in local labour market conditions for people of their age and gender impact their labour market prospects.

The links between the business cycle and individuals' fitness levels is interesting because the effects of the business cycle are ambiguous a priori. Unemployment entails a fall in income, which will reduce fitness, assuming the latter is a normal good. However, unemployment also reduces the price of fitness by reducing the opportunity cost of a person's time, which will increase fitness, assuming fitness is an ordinary good. The magnitudes of these competing effects are likely to vary by age and gender, according to a person's share of household income and how much time they spend on job search and extra household tasks when unemployed, as opposed to leisure. Those with the weakest attachment to the labour market, such as those nearing retirement and those with childcare responsibilities, are likely to experience the biggest drop in the opportunity cost of fitness when they lose their jobs.

Our empirical setting has a number of advantages relative to other studies. Much of the research on fitness is based on studies of elite sports people who are likely very different from most in the population (Papps 2020). Unlike most sports contestants Parkrun participants are likely a reasonably representative sample drawn from the general population, making claims to external validity more credible. Our dependent variable – the time it takes to run 5 kilometres – is an important one from a health perspective and is objectively measured. Running is recognised as one of the most important factors determining heart health (Lee et al. 2014), thus minimising the probability of Ischaemic Heart Disease, which is the leading cause of death among males and second most common cause of death among females in the UK (Owen-Williams 2020). Walking speed is also a predictor of dementia (He et al. 2023), which is the leading cause of death for females and second most common cause of death for males in the UK. Our micro-data are panel data containing an average of around 14 observations per runner, providing sufficient information over time to track within-person fitness responses to changes in labour market conditions whilst also accounting for variance in the propensity to participate in Parkrun. Finally, our estimation sample is sufficient to permit assessments of heterogeneous effects of the business cycle by age and gender which others have shown to be significant in estimating impacts on health behaviours (Di Pietro 2018).

We find no average effect of economic conditions on fitness but this masks considerable heterogeneity by age and gender. Running times improve during recessions for men and women aged 50 and above but worsen for men aged 20-49 and women aged 20-29. Participation in Parkrun is not very sensitive to the business cycle so our results are not driven by compositional change in Parkrunners. These findings imply that the fall in the opportunity costs of fitness during recession is the dominant factor for older runners, since their fitness rises, whereas the income effect induced by unemployment dominates for prime age workers.

The remainder of the paper is set out as follows. In Section 2 we review the current literature and how we contribute to it. Section 3 introduces our dataset. In Section 4 we present our results, and Section 5 concludes.

2. Previous studies

2.1. Mortality

Much of the early research on the impact of the business cycle on health focused on the extensive margin – mortality. Using state-level data for the period 1972-1991, Ruhm (2000) found that mortality rates in the United States were strongly procyclical and were due to declines in motor vehicle accidents and cardiovascular disease during recessions, as well as small reductions in homicides, liver disease, non-motor vehicle accidents and influenza and pneumonia. At the same time there were increases in cancer mortality and suicides. Miller et al. (2009) subsequently confirmed that, among working-age people, most cyclical variation in mortality rates was due to motor vehicle accidents. However, there is a particularly high degree of cyclical variation in mortality rates among those over 65. Stevens et al. (2015) noted that cyclicality was particularly strong among those living in nursing homes and found evidence suggesting that cyclical fluctuations in the quality of health care may be a crucial factor.

The procyclicality of total mortality has been confirmed for other countries (Gerdtham and Ruhm 2006). However, the empirical regularity has subsequently been challenged, first by Ruhm (2015) himself who showed that between 1976 and 2010 total mortality shifted from being strongly procyclical to being largely unrelated to macroeconomic conditions. Whereas deaths from cardiovascular disease and transport accidents continued to be procyclical, cancer mortality and deaths from other causes like non-transport accidents became more countercyclical. He also pointed to methodological issues, arguing that accurate measurement of cyclical effects required data covering at least 15 years.

The other challenge to the procyclicality of mortality has come from the literature pointing to the sensitivity of results to the level of data aggregation. Lindo (2015) shows the sensitivity of estimated business cycle effects for mortality by running analyses at different levels of geographical aggregation. He shows that the procyclicality of mortality weakens as one moves to lower levels of geographical aggregation, explaining the finding in terms of the geographic spillovers in the effects of economic conditions on health outcomes across areas.

Studies using panel micro-data tend to find that worsening economic conditions increase the likelihood of death, particularly among working-age men. For instance, Halliday (2014) shows that for the United States in the 1980s and 1990s a one percentage point increase in the unemployment rate increased the probability of dying within a year of baseline by 6 percent. There was no such relationship for women or the elderly because, the author argues, they had lower labour market attachment.

One paper for the United States seeks to reconcile the individual-level and aggregated data analyses by estimating the mortality effects of both individual unemployment and state-level economic conditions on unemployed and employed individuals in the Panel Study of Income Dynamics (PSID) (Granados et al. 2014). They confirm that individual joblessness has a strong impact in raising mortality probabilities among those who suffer it, whereas recessions have a moderate, albeit significant, impact in reducing mortality rates for both the employed and the unemployed. However, the debate has yet to be settled. Most recently in a study of Swedish working aged men for the period 1993-2007, van den Berg et al. (2017) find mortality is pro-cyclical whether they run analyses at an individual level or aggregate the data to regional level.

A related paper draws attention to heterogeneity in the effects of recession by age, showing the particularly adverse effects exposure to poor market conditions can have for individuals approaching retirement. Using data for the United States over the period 1965-2008 they show that experiencing a recession in one's late 50s reduces employment, health insurance coverage, and health care usage, all of which may contribute to the lower long-term survival probabilities they identify for this group (Coile et al. 2014).

2.2. Health conditions

The effects of the business cycle on aspects of one's health other than mortality are also contested. One study that finds fairly consistent effects is Janke et al. (2020). Using quarterly data for Britain over the period 2002-2016 they show chronic health worsens when economic conditions deteriorate, and that this pattern holds for five broad types of chronic health condition (musculoskeletal, cardiovascular, respiratory, mental health and 'other'). There is spatial heterogeneity in their results with the strongest counter-cyclical effects apparent in the poorest neighbourhoods.[4] On average, their long-run effects – which are reached after two years – imply that a one percent point increase in local employment growth results in around a 2 per cent fall in the prevalence of chronic illness.

Evidence of links between the business cycle and other health conditions is more mixed. For instance, studies come to quite different conclusions in relation to hypertension. Using the huge economic impact of the Great Recession on the Icelandic economy Asgeirsdottir et al. (2014) show that economic crisis affects hypertension among men, but not women, and that the effect was linked to changes in working hours and stress levels, but not to income. For the United States, Seeman et al. (2020) examine the Multi-Ethnic Study of Atherosclerosis and find the Great Recession led to significant increases in blood pressure, with subgroups most severely hit by the recession - such as younger adults still likely to be in the labour force - having larger effects. By contrast, using panel data from the U.S. Health and Retirement Survey 2004-2010 Angrisani and Lee (2016) find the probability of being newly diagnosed with hypertension among adults aged 50 or over rises as local housing market conditions deteriorate. However, they find no association between hypertension and state unemployment rates.

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[4] They recover heterogeneous spatial effects using Global Vector Autoregressive methods which account for feedback across areas while, at the same time, capturing both direct effects of the business cycle on population health and indirect effects arising through interdependent economic and population health influences.

2.3. Health behaviours

As some of the mortality studies above have demonstrated, one mechanism by which economic conditions impacts mortality and health is via health behaviours. Since individuals face reduced opportunity costs associated with investments in healthy behaviours during recessions, one might expect counter-cyclicality in healthy behaviours. However, a recent review of the literature concluded that the evidence linking macroeconomic conditions to smoking, drinking, weight disorders, eating habits and physical activity was "rather mixed" with the only robust finding being a link between economic downturns and a deterioration in mental health (Belles-Obrero and Castello 2018). They identify the variety of empirical methods used, differences in time spans covered, and differences in geographical aggregation model specifications and proxies for macroeconomic conditions as contributing to differences in results across studies.

We might anticipate that one mechanism by which recession may impact health is via the income shock it entails for many. However, using pseudo-panel data from three English cross-sectional studies (the Health Survey for England, the General Household Survey and the Family Expenditure Survey), Adda et al. (2008) find permanent income shocks (up to three years) do not feed through to health outcomes, although they are associated with higher mortality and risky health behaviours (alcohol consumption and smoking). Using data for 2001-2005 from the National Epidemiological Survey on Alcohol and Related Conditions in the United States, Davalos et al. (2012) also find that economic downturns, as indicated by state unemployment rates in the United States, are associated with increased binge drinking, alcohol abuse and dependence. They control for personal income in their main analyses but exclude it in sensitivity checks, producing similar results, suggesting effects may not be driven by income. They contrast their findings with earlier studies finding pro-cyclical effects of alcohol consumption, arguing that their panel analyses which condition on person fixed effects, may be a more appropriate way to capture the effects of the business cycle.

Effects of the cycle on healthy eating are mixed. Analysing micro-data from the US Behavioral Risk Factor Surveillance System (BRFSS) for the period 1990-2009, Dave and Kelly (2012) find higher state-level unemployment is associated with reduced consumption of fruit and vegetables and increased consumption of 'unhealthy' foods like snacks and fast food, the effects being largest for those with the highest predicted probability of being unemployed themselves. They pointed to reduced family income as one channel explaining the procyclicality of healthy eating. However, for the UK Griffith et al. (2016) find shoppers are able to maintain the nutritional quality of what they purchase by adjusting their shopping behaviour to compensate for lower income.

One particularly nice paper by Jofre-Bonet et al. (2017) using the Health Survey for England 2001-2013 considers associations between a range of health outcomes and health-related behaviours and changes in regional unemployment rates, the onset of the Great Recession and, in addition, the interaction between regional unemployment change and the onset of the Great Recession. The onset of the Great Recession was associated with less healthy eating, an increase in Body Mass Index (BMI), increased medicines consumption, and increased likelihood of diabetes and mental health problems. But it was also associated with a reduction in smoking and alcohol intake. Some, but not all, of these effects were attributable to increases in regional unemployment rates. The remainder are linked by the authors to mechanisms such as increased uncertainty and negative expectations.

Sleep is important for health and cognitive function. Using local unemployment rates to capture the business cycle Brochu et al. (2012) find sleep time decreases when the economy picks up. Although this may be problematic for health, Blanchflower and Bryson (2021) point out that both long and short sleep durations can be problematic from a health perspective, so changes in time spent sleeping can have differential effects according to the length of sleep people were previously having. In their study based on micro-data from the BRFSS for the United States for 2009-2019, they show that the unemployed suffer more long and short sleep than the employed and are more likely to suffer from disturbed sleep, and that increases in state-level unemployment result in more short sleep and lower sleep duration. Using the European Social Survey they also find the unemployed are more likely than the employed to suffer 'restless' sleep.

2.4. Physical exercise

Our focus in this paper is taking physical exercise, something which significantly reduces the incidence of cardiovascular disease (Khurshid et al. 2023) and has other health benefits. In addition to cardiovascular benefits noted above it can also positively impact other health outcomes. We focus on Parkrun, an outdoor exercise activity. Using weekly panel data on individuals in the UCL COVID-19 Panel Study Bu et al. (2021) show that outdoor activities like exercise were particularly beneficial in improving mental health and wellbeing during COVID.

Economic conditions may have a bearing on the type and amount of physical exercise individuals take for reasons discussed in the introduction. That exercise may also mitigate adverse impacts of poor economic conditions on individuals' health. Reviewing the literature on the impact of the Great Recession on health and health-related behaviours Margerison-Zilko et al. (2016) note that the evidence regarding its impact on physical activity is mixed. Our review of the evidence also indicates that it is mixed. Using data for Italy over the period 1992-2012 Colombo et al. (2018) find physical activity rises as provincial unemployment rises, as one might expect given the lower opportunity costs in taking exercise in a downturn. Increases in provincial unemployment rates also lead to significant increases in diabetes, infarction, ulcers, cirrhosis and nervous disorders. However, physical exercise dampens these adverse health effects.

In a similar vein Tekin et al. (2013) explore the impact of the 2008 Great Recession on physical exercise and other health-related outcomes. They do so with BRFSS data for the United States for the period 1990 through to 2014. Although, on the whole, they find little effect of the Great Recession on health and health behaviours, they find rising unemployment leads to a significant increase in the likelihood of physical activity, particularly for men. However, analysing micro-data in the Panel Survey of Income Dynamics (PSID) between 2005 and 2015 Alam et al. (2021) find young adults aged between 18 and 27 actually did *less* physical exercise than they did prior to job loss.

Exploiting the American Time Use Surveys for United States over the period 2003-2010 Colman and Dave (2013) are able to distinguish between overall physical activity and recreational exercise. This proves informative because they find that overall physical activity declines with recession, in large part due to reductions in work-related physical exertion, whereas recreational exercise increases. The effects are strongest for lower-educated men who, the authors argue, were in the jobs most adversely impacted by the Great Recession. The results are consistent with a lowering of the opportunity costs of recreational exercise and through the easing of time endowment constraints which are binding when in paid work. Other things equal, this increase in non-work physical activity should lead to health improvements since, according to Saffer et al.'s (2013) analysis of American Time Use Survey data, non-work physical activity is associated with improved health whereas work related physical activity is associated with poorer health.

In a systematic review of the literature on Parkrun Peterson et al. (2022) find participation promotes improvements in fitness, Body Mass Index, physical activity levels, mood and personal wellbeing. But it concluded that "further research is needed to strengthen the knowledge base of the effects of Parkrun to determine its efficacy as a health intervention strategy for physical and mental health" (p. 1486).

None of the studies reviewed by Peterson et al. (2022) examined participation in, or the consequences of, Parkrun over the business cycle, which is the focus of our paper. Most of the rest of the literature on the effects of the cycle on physical exercise tend to focus on the amount of physical exercise undertaken, rather than the intensive margin, namely how fit individuals are. In our paper we are able to do both since we examine participation in Parkrun and the time taken to run 5 kilometres. Furthermore, following Di Pietro (2018) in his paper for Italy, we capture the impact of the business cycle using area-specific unemployment rates by gender and age. As Di Pietro (2018) shows, the procyclical nature of physical exercise is less apparent when one uses these disaggregated unemployment rates as opposed to area-specific unemployment rates for all.

3. Data and Estimation

3.1. Data

To investigate the impact of the business cycle on physical fitness we analyse individual-level panel data on participation in Parkrun (www.parkrun.org.uk). Parkruns are free weekly 5 kilometre running events held around the United Kingdom. Our data consist of 28 million observations on almost 2 million Parkunners between 2004 and 2020. We examine whether physical exercise and fitness levels, as indicated by participation in Parkrun and running times respectively, are affected by the business cycle.

Our individual-level data allow us to track when and where individuals run over time so we can establish patterns of participation and, when they do run, changes in running times. We map in local labour market conditions in the areas people run in and, following Di Pietro (2018), capture variance in those conditions by age and gender to identify heterogeneity in business cycle conditions across different demographic groups. Although the labour market status of runners is unknown to us, we assume that changes in local labour market conditions for people of their age and gender impact their labour market prospects.

Events take place every Saturday morning, as well as on Christmas and New Year's Days. Anyone aged 4 and over can participate; however, to have their time recorded, a runner needs to register online and print out a barcode beforehand. The organisers target participants from all ages and fitness levels, including those who choose to walk rather than run. The first event was held at Bushy Park in London in October 2004 and there are now around 700 locations in the UK (plus hundreds more around the world).[5]

We scraped the universe of individual data from events in the UK from the Parkrun website, from the event's inception until the Covid-19 pandemic forced its suspension in March 2020.[6] Specifically, we collected each person's full history of Parkrun times (in seconds), locations and dates, as well as their gender and age category at the time of each event (4-10, 11-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80+). The total number of observations is 32,901,551. Of these, 2,062,139 observations (or 6%) had to be dropped because they were missing age and/or gender information, almost always due to people running an event but not scanning their barcode at the end and who were therefore listed as "Unknown".

16 is the minimum legal age for employment in the UK. Therefore, we also drop participants under the age of 15 but treat all those in the 15-19 age category as though they were aged 16-19. These

[5] The current locations are shown on the Parkrun website, here: https://www.parkrun.org.uk/events/events.

[6] Parkrun resumed in the UK in July 2021. However, due to the long period of missing data and the fact that the Covid-19 recession differed substantively from previous recessions, March 2020 provides a natural endpoint for the sample period.

restrictions mean the final estimation sample was 16,176,980 observations for men and 12,110,470 observations for women, representing 948,035 unique men and 1,009,825 unique women.

Data on employment rates (the number of people employed divided by the number of people of working age) were obtained from the Annual Population Survey[7] and merged with the Parkrun data, both at the NUTS1 region-quarter level and the region-age category-gender-quarter level. The employment rate varied significantly over the sample period, as shown in Figure 1. The UK experienced a complete business cycle between 2004 and 2020, with the employment rate starting at 72.90% in October 2004, before falling to 70.10% in September 2010, in the aftermath of the Great Recession, and recovering to a high of 76.60% in February 2020, shortly before the first Covid-19 lockdown.

Means of the key variables for men and women are shown in Table 1. As anticipated, men are faster on average than women. Figure 2 depicts the distributions of men's and women's Parkrun times. Both are approximately normally distributed. From Table 1, it is also apparent that the average regional employment rate is substantially lower than the average region-age category-gender cell employment rate.[8] This indicates that Parkrunners disproportionately come from high-employment demographic groups.

3.2. Estimation

We begin by regressing a person *i*'s Parkrun time (in seconds) on date *t*, *TIME*, on the employment rate in that person's region, *ER*, as well as age category, person, location and date fixed effects, separately by gender:

$$TIME_{it} = \alpha ER_{rt} + \lambda_a + \mu_p + \eta_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

[7] For further information on the APS see https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/methodologies/annualpopulationsurveyapsqm.

[8] This is calculated by assigning the cell employment rate to runners then taking the straight average across the sample, so the rate is weighted by the age, location etc. distribution of runners.

where a denotes the age group of person i, p denotes the location of the Parkrun and r denotes the NUTS1 region of that Parkrun. The regressions are run separately by gender g and the standard errors are clustered by region, given that the variation in employment rate occurs at that level.

The employment rate for a region-gender-age category combination provides a better measure of the economic conditions facing a particular person than the regional employment rate. We use this as the measure of business conditions in the regression equation, as follows:

$$TIME_{it} = \alpha ER_{ragt} + \lambda_a + \mu_p + \eta_i + \gamma_t + \varepsilon_{it}. \qquad (2)$$

The cell employment rates allow us to control for location×date fixed effects rather than just separate location and date fixed effects, as follows:

$$TIME_{it} = \alpha ER_{ragt} + \lambda_a + \eta_i + \gamma_{pt} + \varepsilon_{it}, \qquad (3)$$

The location×date fixed effects control for any trend in fitness that varies by location. They also control for variation in weather conditions that might affect running times from week to week in any given place. In equation (3), α is identified by differences in the changes in employment rate across age/gender groups at a given location.

The approach taken above is not unlike that adopted in other micro-studies reviewed in Section Two which also run linear estimators with person and local area fixed effects, although few incorporate national and local area time trends. As in Di Pietro (2018) we examine the sensitivity of results regarding cyclicality by differentiating local labour market conditions for different demographic groups, assuming them to be exogenous with respect to individuals' fitness. Our long timeframe allows us to capture cyclical effects, but we do not examine short- and long-run effects of changes in the cycle on individuals' fitness. Nor do we consider potential heterogeneity in these effects across parts of the country.

Our estimates require that our Parkrun sample is representative of the full population, so that the distribution of Parkrunners across demographic cells and the average fitness within each cell matches that in the population. If this is the case, our results will provide intention-to-treat estimates, reflecting the overall effect of average employment rates on a person's fitness, regardless of his/her actual employment status. However, Angrist and Pischke (2009) show that weighted least squares using group averages coincides with a two-stage least squares (2SLS) regression where a set of group dummies are used as instruments. This means that our results will coincide with those from a 2SLS regression where a set of demographic cell dummies are used as instruments for an individual's employment dummy. Hence, as long as group employment rates have no direct effect on fitness other than by changing individual employment probabilities, our results will not just give intention-to-treat estimates but local average treatment effects of employment on fitness.

4. Results

4.1. Effect of economic conditions on Parkrun times

Columns 1 and 4 of Table 2 indicate that the estimates of α in equation (1) – the coefficient on the employment rate in an individual's region – are insignificant for both men and women. When we switch to using the employment rate within region-gender-age group cells and estimate equation (2), clustering the standard errors by region-gender-age cell, our estimates of α fall markedly, as indicated in column 2 for men and column 5 for women. However, it becomes statistically significant for women. When we estimate equation (3), α (which is identified by differences in changes in employment rates across age/gender groups in a given location) is insignificant and close to zero for both men and women (and in fact is negative for men), as seen in columns 3 and 6 of Table 2.

4.2. Effect of economic conditions on Parkrun participation

The regressions so far rely on runners who continue to participate in Parkrun throughout the business cycle. However, adjustment may also take place at the extensive margin, as people start or stop participating completely in response to economic conditions.

The regressions in Table 2 were rerun but this time for a dependent variable where the dummy variable equals 1 where a person ran a Parkrun in a given week and ran another Parkrun within the next week. This provides an indication of whether a person continues to participate in Parkrun, conditional on appearing at least once. The results are presented in Table 3. As with running times, there is little evidence that economic conditions affect overall participation rates.

4.3. Heterogeneity by age

The results in Tables 2 and 3 suggest that economic conditions have no overall effect on the fitness levels of the population. However, these effects may vary across demographic groups for reasons discussed in Sections 1 and 2. To examine this, we repeat equation (3) interacting the cell employment rate with a person's age group.

There is substantial heterogeneity in the employment rate coefficients across age groups and in contrast to the overall results the coefficients are significant for most age groups, as reported in columns 1 and 3 of Table 4. The solid lines in Figure 3 depict the elasticities of Parkrun time with respect to the local area employment rate by age group and gender at the means of times and employment rates (shown in Table 1). There is evidence of a procyclical pattern of times for men and women aged 50 and above and a countercyclical relationship for women aged 20-29 and men aged 20-49. In other words, recessions improve fitness among older people but worsen fitness among young women and young and middle-aged men.

The effects are quite sizeable. A 10% increase in the employment rate leads to a 0.6% increase in running times among either men or women aged 60-64. However, the same 10% increase in the employment rate leads to a 1.0% reduction in times among men aged 25-29 and a 0.8% reduction in times among women aged 25-29.

The improved running times of older participants when economic conditions deteriorate suggests that the fall in the opportunity costs of fitness during recessions is the dominant factor for this age group, whereas the income effect induced by unemployment dominates for prime age workers. This result is consistent with the finding of Shai (2018), who examines the effects of an increase in the full retirement age for men in Israel in 2004 from 65 to 67 years of age and finds that ceasing work improves health among older men, using multiple health measures.

The participation regression is also re-estimated with age interactions in columns 2 and 4 of Table 4. There is little evidence that participation in Parkrun responds to the business cycle for most age and gender combinations, although there is evidence that a higher employment rate encourages continued participation among those aged 60-64. Hence, the results in columns 1 and 3 are not driven by changes in the composition of the sample over the business cycle.

4.4. Robustness tests

Although Table 3 suggested that the business cycle does not have any effect on Parkrun participation overall, the results in columns 2 and 4 of Table 4 indicate that there may be a significant participation effect among certain age groups. To examine this further, we restricted the sample to people who participated in at least 10 Parkrun events during our sample period. This group of relatively committed runners is unlikely to be as discouraged from participating at the margin as the full sample. However, the coefficients on the employment rate when equation (3) is estimated using the restricted sample are very similar to those for the full sample, as seen in columns 1 and 4 of Table 5.

The employment rate captures the fraction of people in the population who work in any given period. Hence, it does not distinguish between the labour force status of the remainder. Those who are unemployed (and are actively engaged in job search) presumably value their non-work time less than those who are not in the labour force. To examine this further, we repeat the regression from columns 1 and 3 of Table 4 using the activity rate for each age group/gender/region/quarter, that is, the fraction of the working age population that is either employed or unemployed. The results are reported in columns 2 and 5 of Table 5. Among women of all ages and men over 50, the elasticities are very similar to those found with the employment rate. For men under 50, the elasticities are considerably larger than in Table 4 and there are no longer any significant negative effects. This implies that the harmful effects of recessions on fitness among young and middle-aged men are driven by people being pushed from employment into unemployment, rather than out of the labour force completely.

Many runners participate in Parkrun events in other parts of the UK throughout the year. However, any effect of the business cycle may be driven by economic conditions in the place in which they live, not where they choose to run and the probability of a person travelling to another location is likely to be affected by their economic situation. To address this, we estimated a person's "home location" by calculating their modal Parkrun location each year. Using home location rather than actual location made little difference to the results in Table 4 (as seen in columns 3 and 6 of Table 5).

4.5. Including sampling weights

Since we do not have information on the actual employment status of the individuals in our sample, our regressions are effectively reduced form. As long as the employment rate among the Parkrun sample is equal to the overall employment rate in each region-gender-age category-year cell, our coefficient will coincide with the coefficient from a 2SLS regression, where the employment rate is used as instrument for actual employment status (Angrist and Pischke 2009).[9] However, the sample of Parkrunners may be unrepresentative of the working age population. For instance, they may be more focused on physical fitness than the population at large (Reece et al. 2022). To address this, we reweight the data so that the average characteristics in the sample more closely reflect those in the full population.

Participation in Parkrun grew rapidly throughout the sample period, meaning that our sample overrepresents more recent years. There were only 1,590 runs by men and 483 runs by women in 2005, the first full year in the sample, when there was only one Parkrun location. By 2019, these had increased to 3,341,786 and 2,678,664, respectively. To correct for this, we weighted the observations so that each year was weighted equally. As seen in columns 1 and 4 of Table 6, this made little difference to the estimated coefficients.

Stevinson and Hickson (2013) examined participation in Parkrun and found that "non-runners, with women, older adults and overweight people [were] well represented". However, naturally, Parkrunners are a self-selected sample. To control for the fact that our sample is not truly representative of the wider population in terms of demographic characteristics, we constructed a

[9] Ignoring the fixed effects, the reduced form coefficient is equal to $\mathrm{cov}(z,y)/\mathrm{var}(z)$ and the instrumental variables coefficient is $\mathrm{cov}(z,y)/\mathrm{cov}(z,x)$, where y is Parkrun time, x is an employment status dummy and z is the region-age category-gender cell employment rate, which is the average of x within each cell. Assuming that the sample averages are the same as the population averages within each cell, $\mathrm{cov}(z,x)=\mathrm{var}(z)$, meaning that the two estimators coincide.

set of sampling weights, equal to the 2012 population estimate from the Annual Population Survey for a given gender/age category/NUTS1 region cell divided by the number of Parkrunners in that cell, week by week. As seen in columns 2 and 5 of Table 6, estimating equation (3) using these weights results in a similar pattern of coefficients across ages as before. However, the employment rate coefficients are now substantially more negative for men aged 25-59 and women aged 20-34.

Since Parkrunners are a self-selecting sample, they are also likely to have better inherent fitness levels than the population as a whole. It is therefore possible that the pattern seen in Figure 3 does not hold among non-Parkrunners. Further, the degree of self-selection may vary from group to group, potentially affecting the shape of the estimated age profiles. We can examine whether this is the case by exploiting the fact that Parkrun attracts people of a very wide range of fitness levels, including those well below the average for their age and gender.

Parkrun provides an "age grade" for each runner, each week. Although the exact way the grade is calculated is not disclosed by Parkrun, this purports to express each Parkrun result as a percentage of the world record performance, given a person's age and gender.[10] Accordingly, a grade of 100% should indicate approximately a world record for that age and gender. Conversely, a grade of 60-70% is said to denote a performance of "local class level". We consider a grade of 50% to identify a person of median fitness within the wider population.[11] A grade of 50% is equivalent to a 5 km time of 27:18 for a man aged 40 and 30:36 for a woman aged 40. We calculate each runner's median grade over the sample period and classify each as "fit" (those with a median grade equal to 50% or above) or "unfit" (those with a median grade below 50%). In columns 3 and 6 of Table 6 we modify the sampling weights so that the weighted fraction of fit people within each cell is 0.5. Using the modified weights makes little difference compared to using the region-gender-age-year weights. The elasticities of time with respect to employment rate are depicted by the dotted lines in Figure 3. As noted above, substantially larger negative elasticities are found for young women and young and middle-aged men, compared to the unweighted regressions run earlier.

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[10] Details are given at https://support.parkrun.com/hc/en-us/articles/200565263-What-is-age-grading-.

[11] Using 40% or 60% as the median makes little difference to the results.

5. Conclusion

In this paper we examine whether fitness is affected by labour market conditions, drawing on 28 million observations on people's 5 kilometre running times at Parkrun, a free weekly event held around the UK. This represents information on almost 2 million people participating in Parkrun and is relatively representative of the distribution of age and fitness levels in the population. Since we have longitudinal data, we are able to examine how a given person's fitness level changes over time, rather than relying on across-person comparisons which are potentially fraught with confounding factors. Our objective measure of fitness also avoids the problems associated with self-reported health. Finally, we are able to examine how the business cycle affects both the extensive (participation) and intensive (running time) margins, providing a more complete picture than previous studies.

Recessions are found to improve running times for men and women aged over 50, but to worsen times for men aged 20-49 and women aged 20-29. Participation in Parkrun is not found to be very sensitive to economic conditions and a range of robustness checks are carried out. These age differences appear to be associated with movements into unemployment from employment, rather than by runners exiting the labour market entirely.

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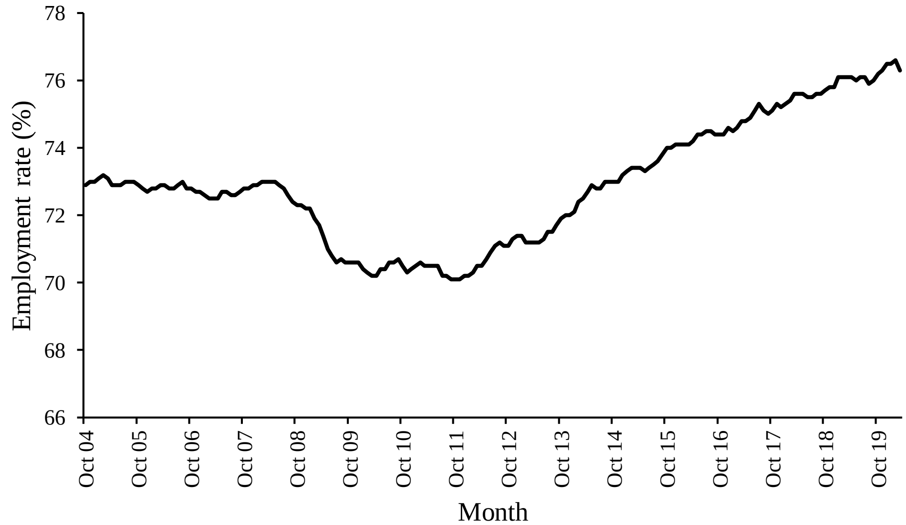
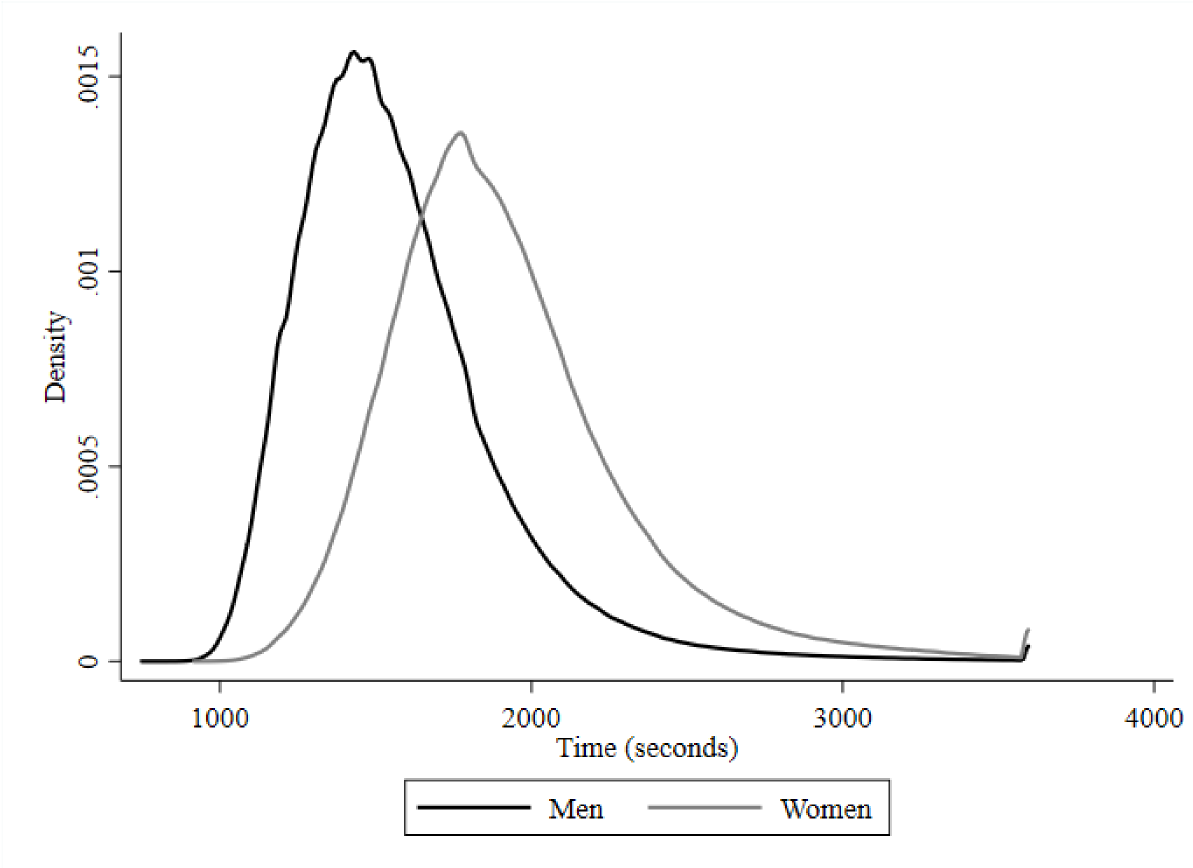
Figure 1: UK employment rate, 2004-2020



Source: Office for National Statistics, Labour Force Survey.

Figure 2: Distribution of Parkrun times by gender



Notes: Data from parkrun.org.uk.
Values are right-censored at 60 minutes.

Figure 3: Running time-employment rate relationship by gender and age

Notes: Markers indicate elasticities that are significant at the 5% level.

Table 1: Means for the estimation sample

Variable	Men	Women
Time (seconds)	1,567.325	1,912.166
Participated in following week	0.488	0.437
Median age grade	57.318	52.682
Regional employment rate (%)	60.258	60.308
Cell employment rate (%)	79.883	72.372
Aged 16-19	0.039	0.033
Aged 20-24	0.036	0.049
Aged 25-29	0.072	0.096
Aged 30-34	0.101	0.114
Aged 35-39	0.117	0.132
Aged 40-44	0.140	0.153
Aged 45-49	0.161	0.160
Aged 50-54	0.138	0.125
Aged 55-59	0.091	0.076
Aged 60-64	0.052	0.037
Aged 65-69	0.030	0.018
Aged 70-74	0.015	0.006
Aged 75-79	0.005	0.001
Aged 80+	0.002	0.000
Number of individuals	948,036	1,009,826
Number of observations	16,176,980	12,110,470

Table 2: Running time regressions

Variable	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Regional employment rate	0.872			1.104		
	(0.579)			(1.162)		
Cell employment rate		0.078	-0.013		0.209**	0.007
		(0.093)	(0.084)		(0.095)	(0.084)
Location fixed effects	Yes	Yes	No	Yes	Yes	No
Date fixed effects	Yes	Yes	No	Yes	Yes	No
Location × date fixed effects	No	No	Yes	No	No	Yes
R squared	0.702	0.702	0.727	0.738	0.738	0.756
Number of observations	16,176,980	16,176,980	16,176,980	12,110,470	12,110,470	12,110,470

Notes: All specifications also include age and person fixed effects. Standard errors are clustered by region in columns 1 and 4 and by region-gender-age group cell in columns 2-3 and 5-6 and are presented in parentheses. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table 3: Participation regressions

Variable	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Regional employment rate	0.003			0.003		
	(0.002)			(0.002)		
Cell employment rate		0.000	-0.000		0.000**	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Location fixed effects	Yes	Yes	No	Yes	Yes	No
Date fixed effects	Yes	Yes	No	Yes	Yes	No
Location × date fixed effects	No	No	Yes	No	No	Yes
R squared	0.206	0.206	0.228	0.201	0.201	0.228
Number of observations	16,120,384	16,120,384	16,120,384	12,064,358	12,064,358	12,064,358

Notes: All specifications also include age and person fixed effects. Standard errors are clustered by region in columns 1 and 4 and by region-gender-age group cell in columns 2-3 and 5-6 and are presented in parentheses. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table 4: Heterogeneity in employment rate coefficients by age

Coefficient on cell employment rate	Men		Women	
	(1)	(2)	(3)	(4)
	Time	Participation	Time	Participation
Aged 16-19	-1.342***	-0.002***	-0.882***	-0.001***
	(0.187)	(0.000)	(0.186)	(0.000)
Aged 20-24	-1.103***	-0.001**	-1.819***	-0.000
	(0.161)	(0.000)	(0.164)	(0.000)
Aged 25-29	-1.742***	-0.001	-1.915***	-0.000
	(0.176)	(0.000)	(0.173)	(0.000)
Aged 30-34	-1.186***	-0.001	-0.159	-0.000
	(0.176)	(0.000)	(0.190)	(0.000)
Aged 35-39	-0.974***	-0.000	0.143	-0.000
	(0.173)	(0.000)	(0.180)	(0.000)
Aged 40-44	-0.958***	-0.000	-0.313**	0.000
	(0.174)	(0.000)	(0.152)	(0.000)
Aged 45-49	-0.500***	0.000	0.026	0.000
	(0.169)	(0.000)	(0.171)	(0.000)
Aged 50-54	0.433***	0.000	0.922***	0.000
	(0.146)	(0.000)	(0.204)	(0.000)
Aged 55-59	0.947***	0.001***	1.523***	0.001*
	(0.156)	(0.000)	(0.211)	(0.000)
Aged 60-64	1.843***	0.001***	2.642***	0.002***
	(0.175)	(0.000)	(0.192)	(0.000)
Aged 65-69	2.291***	0.001***	4.404***	0.000
	(0.292)	(0.000)	(0.489)	(0.001)
Aged 70-74	6.410***	0.002***	6.566***	0.003**
	(0.568)	(0.001)	(1.324)	(0.001)
Aged 75-79	6.901***	0.002**	9.582***	-0.007
	(1.248)	(0.001)	(2.645)	(0.004)
Aged 80 plus	14.919**	-0.001	29.316	0.003
	(6.463)	(0.004)	(18.392)	(0.015)
R squared	0.727	0.228	0.756	0.228
Number of observations	16,176,980	16,120,384	12,110,470	12,064,358

Notes: All specifications also include age, person and location × date fixed effects. Standard errors are clustered by region-gender-age group cell and are presented in parentheses. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table 5: Robustness tests for running time

Coefficient on cell employment/ activity rate	Men			Women		
	(1) More than 10 runs	(2) Activity rate	(3) Home location	(4) More than 10 runs	(5) Activity rate	(6) Home location
Aged 16-19	-1.516***	0.490***	-1.915***	-0.887***	-0.038	-1.241***
	(0.200)	(0.176)	(0.221)	(0.210)	(0.182)	(0.234)
Aged 20-24	-1.165***	0.686***	-1.378***	-1.518***	-1.092***	-2.148***
	(0.199)	(0.180)	(0.179)	(0.193)	(0.194)	(0.186)
Aged 25-29	-1.535***	-0.199	-1.924***	-1.395***	-1.662***	-2.091***
	(0.190)	(0.278)	(0.191)	(0.182)	(0.202)	(0.198)
Aged 30-34	-1.186***	0.299	-1.437***	-0.289	0.015	-0.163
	(0.183)	(0.237)	(0.194)	(0.197)	(0.219)	(0.222)
Aged 35-39	-1.446***	0.074	-1.267***	0.030	0.274	0.049
	(0.183)	(0.221)	(0.194)	(0.186)	(0.193)	(0.204)
Aged 40-44	-1.338***	0.170	-1.151***	-0.459***	-0.212	-0.266
	(0.170)	(0.225)	(0.188)	(0.140)	(0.175)	(0.174)
Aged 45-49	-0.682***	0.273	-0.666***	-0.088	0.035	0.030
	(0.150)	(0.201)	(0.188)	(0.150)	(0.201)	(0.207)
Aged 50-54	0.158	0.544***	0.449***	0.783***	0.783***	1.092***
	(0.125)	(0.170)	(0.166)	(0.183)	(0.219)	(0.239)
Aged 55-59	0.750***	0.779***	1.128***	1.039***	1.409***	1.699***
	(0.133)	(0.196)	(0.175)	(0.187)	(0.230)	(0.232)
Aged 60-64	1.574***	1.781***	2.139***	2.386***	2.534***	2.818***
	(0.159)	(0.182)	(0.197)	(0.178)	(0.186)	(0.206)
Aged 65-69	1.998***	2.165***	2.652***	4.364***	4.306***	5.092***
	(0.270)	(0.279)	(0.339)	(0.455)	(0.488)	(0.552)
Aged 70-74	5.964***	6.428***	7.378***	6.525***	6.225***	6.942***
	(0.553)	(0.555)	(0.642)	(1.214)	(1.317)	(1.505)
Aged 75-79	6.810***	6.628***	7.513***	9.170***	8.448***	9.692***
	(1.181)	(1.253)	(1.280)	(2.480)	(2.614)	(2.865)
Aged 80 plus	15.320**	13.804**	13.317**	44.981**	34.083	29.341
	(6.557)	(6.772)	(6.589)	(19.145)	(21.746)	(19.170)
R squared	0.705	0.727	0.719	0.713	0.756	0.750
Number of observations	11,288,454	16,176,980	15,625,715	7,481,189	12,110,470	11,721,478

Notes: All specifications also include age, person and location × date fixed effects. Standard errors are clustered by region-gender-age group cell and are presented in parentheses. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.

Table 6: Weighted regressions for running times

Coefficient on cell employment rate	Men (1) Year weights	Men (2) Demographic weights	Men (3) Fitness weights	Women (4) Year weights	Women (5) Demographic weights	Women (6) Fitness weights
Aged 16-19	-1.273***	-0.936***	-0.834***	-0.447	-1.262***	-1.151***
	(0.436)	(0.253)	(0.252)	(0.291)	(0.219)	(0.223)
Aged 20-24	-0.392	-1.296***	-1.525***	-0.402	-2.326***	-2.177***
	(0.623)	(0.197)	(0.226)	(0.556)	(0.201)	(0.203)
Aged 25-29	-1.871***	-2.989***	-3.065***	-2.379***	-3.559***	-3.282***
	(0.292)	(0.241)	(0.284)	(0.576)	(0.250)	(0.241)
Aged 30-34	-1.176***	-2.233***	-1.891***	0.255	-2.212***	-2.061***
	(0.339)	(0.261)	(0.344)	(0.551)	(0.277)	(0.275)
Aged 35-39	-0.974***	-2.571***	-2.376***	0.474	-1.600***	-0.947***
	(0.304)	(0.261)	(0.348)	(0.490)	(0.258)	(0.279)
Aged 40-44	-1.002**	-2.385***	-2.539***	0.769	-1.725***	-1.063***
	(0.463)	(0.263)	(0.339)	(0.549)	(0.233)	(0.243)
Aged 45-49	0.347	-1.682***	-1.022***	1.393***	-1.172***	-1.061***
	(0.440)	(0.272)	(0.322)	(0.534)	(0.280)	(0.320)
Aged 50-54	0.307	-0.679***	0.246	2.823***	0.154	0.898***
	(0.291)	(0.214)	(0.356)	(0.570)	(0.316)	(0.340)
Aged 55-59	1.071***	0.387*	1.366***	3.747***	1.070***	2.797***
	(0.236)	(0.209)	(0.370)	(0.564)	(0.341)	(0.463)
Aged 60-64	1.184***	0.186	0.214	1.967***	1.757***	2.347***
	(0.265)	(0.247)	(0.398)	(0.369)	(0.215)	(0.268)
Aged 65-69	2.793***	2.308***	1.385***	4.359***	2.950***	3.291***
	(0.382)	(0.295)	(0.401)	(0.900)	(0.497)	(0.594)
Aged 70-74	10.798***	8.192***	7.374***	6.442***	7.308***	9.024***
	(0.975)	(0.624)	(0.735)	(2.092)	(1.150)	(1.175)
Aged 75-79	9.814***	8.036***	8.869***	-10.481**	6.326**	6.155***
	(1.423)	(1.225)	(1.384)	(5.107)	(2.557)	(2.356)
Aged 80 plus	15.454	11.034**	11.797**	54.499***	36.652**	32.384*
	(9.425)	(4.854)	(4.790)	(20.563)	(15.523)	(16.755)
R squared	0.777	0.826	0.846	0.827	0.852	0.869
Number of observations	16,176,980	16,176,980	16,176,980	12,110,470	12,110,470	12,110,470

Notes: All specifications also include age, person and location × date fixed effects.

Standard errors are clustered by region-gender-age group cell and are presented in parentheses. *, ** and *** denotes significance at the 10%, 5% and 1% level, respectively.