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The effect of task switching on productivity: evidence from major league baseball pitchers

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Abstract

There are few opportunities, outside of a laboratory setting, to study how workers respond to the demands of task switching. A priori, task switching might either harm or benefit productivity, and thus it becomes an empirical question. Faced with difficulties in the measurement of productivity and task switching, we turn to an industry that produces accurate, detailed, and comparable measures of worker production, namely starting pitchers in Major League Baseball. Our results suggest that task switching, between pitching and batting, can improve subsequent pitching performance, though heterogeneity in this effect is present. We discuss implications for wider labour market settings.

Keywords: labour productivity; task switching; baseball; coarsened exact matching.
JEL classifications: J24, M54, Z21, Z22

1. Introduction

Managers should be greatly interested in how fatigue affects the productivity of workers. Over the course of a working day, workers might become mentally and/or physically fatigued, possibly leading to productivity losses. Hart (2004) proposes that the marginal productivity of hours worked varies over the course of the working day. In fact, at the start of the day, it could be that marginal productivity actually rises as workers 'warm up', but eventually fatigue or boredom sets in and productivity falls.

One possible source of fatigue comes from the requirement for workers to carry out multiple tasks (see e.g. Russ and Crews 2014). Most, if not all, jobs or other daily activities such as household production (Kalenkoski and Foster 2015) involve some degree of switching between different tasks. These may be job-related (e.g. checking work emails, attending meetings, speaking to clients, etc.) or not (e.g. checking mobile phones, checking sports news, etc.). However, changing tasks is likely to involve a switching cost, perhaps in the form of a mental adjustment to adapt to a new task or through lost productive time whilst switching. Indeed, a body of literature from psychology and behavioural economics (e.g. Buser and Peter 2012) suggests subjects tend to struggle when faced with such demands.

However, there has been little empirical research from observational studies of workers in the field to understand how (or indeed if) task switching affects productivity and performance. This, in part, is due to the lack of detailed worker-level productivity data because defining productivity in many occupations is not a straightforward task. Even if accurate productivity measures are available, it is rare to observe them on a frequent enough basis to track changes over short spaces of time.

To address these shortcomings in measurement, we use a particularly rich micro-level dataset containing accurate and comparable measures of worker performance and indicators of task switching to estimate its effect on output. The industry is professional baseball, specifically Major League Baseball (MLB), and the workers under consideration are starting pitchers. Economists have often turned to sports to overcome data limitations and with good reason (for a discussion, see Bar-Eli, Krumer, and Morgulev 2020).

Specifically, we test how pitching performance (measured using a variety of outcomes) changes following a pitcher's own at-bat. Hence, the treatment is whether the pitcher was batting and/or got on base in the previous half inning. Control observations are then pitchers who did not bat previously. To address endogeneity concerns related to the decision to pull a starting pitcher, we use coarsened exact matching (CEM; Iacus, King, and Porro 2012) by matching on at-bats that are alike with respect to variables that predict a starting pitcher being pulled. The possible identification problem exists in that we might only observe pitchers being allowed to carry on to bat if they are performing well in general. Thus, there would be a positive correlation between batting and pitching performance. However, we usually observe pitchers batting at least twice during a game; starting pitchers, on average, first bat around the third inning/54th pitch and are pulled around the 6th inning/89th pitch.

Contrary to expectations, we find a small but positive effect of previously batting. The velocity of fastballs increases after batting, though substantial heterogeneity exists depending on the outcome of the at-bat. We expand upon these estimates with various robustness checks seeking to identify the source of improvement through task-switching.

The remainder of the article is structured as follows. Section 2 reviews the literature on the effects of fatigue and task switching on productivity. Section 3 offers an overview of baseball and MLB. Section 4 describes the data, our measures of task switching, and outlines our estimation strategy. Section 5 presents the results and Section 6 concludes our work by discussing implications of these findings for MLB and more broadly.

2. Theory and literature review

We contribute to a number of strands of literature with a particular focus on the effects of fatigue and task switching on performance. Although our focus is on baseball, we argue that our findings are generalizable not only to other sports, but also to more general labour market settings, particularly jobs that involve carrying out physical tasks with accuracy. Construction work is one good example, where typically workers are carrying out physically demanding tasks (lifting, carrying, etc.) on a frequent basis, and often with millimetre precision. Likewise, baseball pitchers are carrying out strenuous and repetitive work where small margins can be the difference between success and failure.

Research examining the effects of fatigue on performance tends to focus on the association between hours worked and output. For example, Pencavel (2015) considers the case of munition factory workers during the First World War in Britain where exogenous variation in hours worked was driven by the demand for shells on the front line. Increases in output were proportional to hours worked up to about 48 h of work per week, but working beyond this led to diminishing marginal product of hours. Collewet and Sauermann (2017) also uncover diminishing marginal productivity of hours for workers in a Dutch call centre. However, not all research finds evidence of this negative association. Lu and Lu (2017) find the opposite to be true following the abolition of mandatory overtime for nurses in nursing homes, while Crocker and Horst (1981) found no evidence of a decline in marginal value product associated with daily hours of work for citrus fruit pickers in California.[1]

Most sports economics literature on fatigue and performance examines the role of rest days between fixtures rather than within-game fatigue (which would be more akin to the effect of extended hours). Scoppa (2015), for the case of international football (soccer) tournaments, and Entine and Small (2008), for the case of the National Basketball Association, are notable studies. Examination of within game fatigue is confined mainly to the sports medicine literature (see, e.g. Rampinini et al., 2009 on Italy's Serie A). There is also a well-established literature examining muscular fatigue of baseball pitchers (Murray et al., 2001; Escamilla et al., 2007), though many studies suffer from small sample sizes and are limited to laboratory setups rather than observing game data.

In addition to fatigue, other studies have investigated the role of task switching and multitasking, each distinct behaviour, on productivity. Multitasking involves carrying out different tasks simultaneously, while task switching involves carrying out different tasks sequentially. Buser and Peter (2012) show that this distinction is important. Their experiment randomly allocates participants into three groups: one multitasking, one task switching at a time determined by the experiment, and a final group task switching at their convenience.[2] Results suggest that subjects who multitasked perform worse than those who task switch, while surprisingly, being able to pick when to switch tasks was associated with worse performance.

It is unclear whether such experimental evidence translates into the real world because of the nature of the tasks involved. Jobs involving multitasking or task switching are now synonymous with modern day work, and thus it should be of great interest to managers to understand how (or if) it affects productivity. Sports also offer several examples of players having to do different tasks. In football (soccer) and rugby, for example, players are constantly switching between attacking and defending whenever ball possession changes, while in cricket and baseball, players are required to both field and bat.

Aral, Brynjolfsson, and Van Alstyne (2012) suggest task switching has ambiguous effects on productivity. On the one hand, an effective ability to task switch could allow workers to smooth their output during lulls in workload, while skill complementarities across tasks should benefit productivity. On the other hand, carrying out multiple tasks could cause delays and force prioritizing more important tasks, while switching between tasks is also associated with mental congestion and increased errors (see, e.g. Rubinstein, Meyer, and Evans 2001, or Kiesel et al., 2010).

Turning to industry-specific evidence, Coviello, Ichino, and Persico (2015) use a sample of Italian judges specializing in labour disputes who receive randomly assigned cases. Naturally, some of these cases are more complex and take longer to complete. Judges respond to an increase in future workloads by juggling more cases in the present. In particular, a 1 per cent exogenous increase in workload increases the duration of trials by between 3 and 6 days, and judges would need to increase their effort by between 1.1 per cent and 1.4 per cent to maintain the same length of trials. Aral, Brynjolfsson, and Van Alstyne (2012) report a similar result on project outputs at an IT firm, while Singh (2014)

1 This does raise a potentially important distinction between mental and physical fatigue. Fruit picking is unlikely to be mentally challenging but is likely to be physically demanding. Other occupations will differ and may involve an interaction of the two. Marcora, Staiano, and Manning (2009) show this distinction is important; mental fatigue can impair physical performance and limits short-term endurance through perception of higher effort.

2 In their experiment, the tasks included a Sudoku puzzle and a word search game.

reports mixed evidence on the benefits of task switching from a hospital emergency department.[3]

In the domain of MLB, Bond and Poskanser (2023) pose a very similar question to our own. They find that pitchers who had recently batted were more likely to get the batters they faced out in the subsequent inning, a result which disappears after three at-bats, however.[4] Our article differs along several dimensions, and we believe these represent an improvement on both data and methodological fronts, which we outline below. First, we consider data at a pitch level rather than an at-bat level, allowing us to observe more variability in pitcher performance. Importantly, we also consider several more precise and objective indicators of performance, primarily overall velocity and fastball velocity. Bond and Poskanser (2023) consider batters getting out, which is partly dependent on batter quality, luck, pitch quality, and fielding support. While Bond and Poskanser control for various relevant fixed effects, such as for the individual pitcher, our estimates also include batter fixed effects, amongst others, to control for unobserved differences across batters. It is also unclear whether Bond and Poskanser (2023) use all pitchers or only starting pitchers in their analysis. This distinction is important since it is unlikely that relief pitchers (pitchers who replace the starter) have enough time in a game for observable counterfactual opportunities, with very few relief pitchers ever batting in games. Finally, it is worth discussing the potential endogeneity concern behind their estimated effect disappearing after three batters. In particular, half innings that extend beyond the third at-bat are a signal of poor performance—pitchers that went three up and three down in the inning would not be observed past the third at-bat. Hence, any effect disappearing after three at-bats could be because these pitchers should have been pulled at that point. In short, this represents a possible mistake by the manager not to pull the pitcher earlier rather than a diminishing effect of batting on pitcher performance.

More generally, what are the benefits of using sports data to address such a question? First, a common issue in the assessment of performance in non-sports settings is that it can prove difficult to compare performance across different workers and firms. Moreover, performance on any task may encapsulate several dimensions, for example, quantity of output, quality of output, or some combination of the two. In baseball, however, performance metrics are easily comparable across workers (in our case, pitchers) and firms (in our case, teams). Even though a pitch has several dimensions of quality, each provides a very clean assessment of performance, meaning pitches can be objectively assessed. Furthermore, the inherent structure of a game of baseball consisting of innings and a batting order makes it easy to identify a player's different roles, and this clear structure allows us to identify changes to performance in response to task switching. Perhaps most importantly, we are considering a high-stakes setting where decisions have real and sizeable effects on the outcomes of matches, and agent objectives are well-known ahead of time.

3. Industry context: baseball and MLB

Baseball is a team sport played between two opposing teams, with each team sequentially batting and fielding. The game proceeds when a pitcher (one of nine positions on the defensive, or fielding team), standing on the pitcher's mound, throws to the batter, standing at home plate. The batter continues to be pitched at until one of three possible outcomes: following three strikes (i.e. three pitches thrown through the strike zone and called a strike by the umpire and/or the batter swinging at any pitch), getting out when hitting a ball into play, getting on base (either via hitting the ball into play, a walk, hit by pitch, or catcher interference), or hitting a home run. The aim of the batter is to score runs by advancing

[3] In the case of Singh (2014), task switching refers to attending to patients with different ailments.
[4] An at-bat refers to a batter's turn to bat against a pitcher.

around three bases and back to home plate, while the pitcher and his teammates seek to prevent the batter from advancing between bases.

A game lasts nine innings in regulation, during which each team plays both offense and defence, and the team with the most runs wins the game.[5] Each inning consists of two half innings: a top (first) and bottom (second) half. In the top half, the home team pitches and the away team bats, and vice versa for the bottom half. A half-inning consists of three outs (three players from the batting team getting out). As such, players on both teams are required to play offense and defence.

MLB is the highest level of professional baseball and consists of 30 teams who play 162 regular season games, spanning from early April until late September.[6] Teams are split into the American League (AL) and the National League (NL). Since 1903, these leagues have cooperated to run a single season-ending championship (the World Series), but only in 2000 did the leagues merge into a single organization. Though scheduling rules changed in 2023, as of 2022 scheduling rules were that teams play 142 games against teams from the same league, and the remaining 20 are inter-league games. Teams play an equal number of home and away games.

Since 2021, both leagues have operated under identical rules.[7] During our time frame of analysis, however, that is, 2019 and earlier, there was one key difference between the leagues, and this difference is crucial to our definition of task switching. Since 1973, the AL had operated under the Designated Hitter (DH) rule, allowing teams in the AL to nominate a player, the DH, to replace one player in the batting order. This is the DH's only role; they do not play any position on defence. As pitchers are customarily poor hitters, it is usually they who are replaced by the DH in the batting order. The NL, on the other hand, did not use this rule before 2020.[8] The 2020 Collective Bargaining Agreement saw an end to this difference, and league rules were harmonized such that both leagues now operate under the DH.

Hence, before 2020, in the NL, we could observe pitchers having to both pitch (their primary role) and bat in an attempt to advance round bases. Whereas in the AL, pitchers only pitched; they did not bat. Unlike other baseball leagues, MLB was rare in making some of its pitchers bat. High school and collegiate-level baseball usually adopt some variation of the DH rule. The Central League, one of two leagues in Japan's Nippon Professional Baseball League, is the other notable exception where pitchers are required to bat.[9]

The theoretical and empirical evidence presented in the previous section has implications for how we might expect pitchers to respond to the demands of batting. On the one hand, batting requires additional physical effort, and so might induce additional fatigue on pitchers. Performance in their primary role, pitching, might suffer as a result. This might be particularly true if they are successful at-bat and are required to sprint to reach bases. On the contrary, batting might act as a break from the core task and means pitchers avoid sitting on the sidelines, potentially stiffening up, dwelling on any recent mistakes, etc., between

[5] If the game is tied after nine innings, additional innings are played until one team is ahead at the end of a given inning.

[6] This represents an intense schedule for teams and players, with games taking place on a far more frequent basis than other major global sports leagues. For example, in the National Football League, teams play seventeen games over a 4 month period (September to December/early January), teams in the National Basketball League play eighty-two games over a 7 month period (October to April), while European football (soccer) leagues run from August to May with teams playing in the region of 34–38 games.

[7] The 2020 season also operated under identical rules, though this was a severely shortened and altered season because of COVID-19. The season was shortened to sixty games and teams were subjected to many temporary rule changes, including the adoption of a universal DH rule.

[8] During interleague play (i.e. an AL versus NL team), the DH rule was operational if the game was played at an AL ballpark.

[9] The DH rule was originally adopted by the AL as an experiment in the face of low offensive output. Since fans value offensive output, the removal of a poor hitter might boost attendances and ultimately revenues (Domazlicky and Kerr 1990).

innings. Hence, this might serve as an opportunity to regain focus and stay physically active and loose, with pitching performance potentially improving as a result.

4. Data and estimation

We examine pitch-by-pitch data for regular season MLB games for the 2017, 2018, and 2019 seasons, sourced from Baseball Savant (https://baseballsavant.mlb.com/). Our analysis begins in 2017 to avoid conflating changes in pitcher performance with changes in pitch measurement. Before 2017, different technology was used to record the pitch characteristics. Our analysis period ends with the 2019 season because the COVID-19 pandemic affected the 2020 season. The data are nevertheless very large, with 7,290 games and approximately 2.1 million individual pitches. The data include various characteristics of each pitch, including pitch velocity and location, as well as information about the outcome of each play (e.g. score, players on base). This information is captured in game by Trackman, a system of high accuracy radars and cameras to track player and ball movements. Using these data, we construct various outcomes of pitcher performance and define measures of both in game fatigue and task switching.

We limit our analysis to starting pitchers, reducing our sample to about 1.3 million pitches. A total of 551 starting pitchers, from both the AL and NL appear in our sample. We make this limitation because relief pitchers rarely get a chance to bat or get on base, so there are far fewer observed counterfactual opportunities.

4.1 Pitcher performance

Baseball is well known for producing a multitude of statistics for evaluating player performance. Key to this study, however, is choosing outcomes that are independent (as much as possible) of the batter or luck in batting outcomes, but reflective of underlying pitching performance and current fatigue. The most obvious choice is pitch velocity, measured at the point of release, because fatigued pitchers will not be able to throw as hard as a fully rested pitcher (Suchomel and Bailey 2014). Velocity is also the outcome of choice in many sports science studies on pitcher fatigue, particularly those studying injury risk amongst pitchers (see, e.g. Bushnell et al. 2010; Keller et al. 2016). Perhaps most importantly, the use of velocity as the primary performance indicator allows us to limit the extent to which any change in offensive output against the pitcher is caused by being allowed to go back out when the other team might be at the bottom of its batting order.

Not only will velocity be affected by pitcher fatigue but also by strategy. Pitchers might purposely throw a slower pitch (such as a changeup or a curveball) after a sequence of fastballs to provoke the batter to swing too early and induce poor contact. A ‘swing and miss’ is equivalent to a strike for the pitcher. Hence, in any model of pitch velocity, controlling for the type of pitch will be important.[10] Our preferred specifications for velocity models rely on fastballs only. Over half of the 1.3 million pitches are categorized as a fastball, leaving us with just under 760,000 observations in the fastball sample.[11] Figure 1 charts the probability of pitchers throwing a fastball as the game progresses. While the first pitch is very likely to be a fastball, very quickly the probability drops to around 55–60 per cent. Given this relative stability, any results should not be driven by pitch selection. More specifically, the choice of whether or not to throw a fastball should not be driven by our key variables of interest that is, variables capturing task switching (which we define in the following section).

[10] The type of pitch is classified according to Statcast’s algorithm, taking into account velocity, spin, movement, and direction. Statcast lists a total of five pitch types.

[11] Four-Seam Fastballs (code FF), Two-Seam Fastballs (FT), Sinkers (SI), and Cutters (FC) are classed as fastballs.

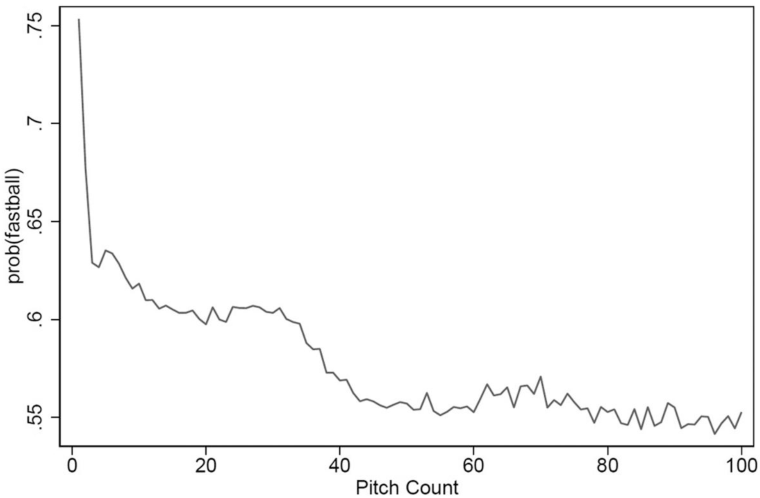

Figure 1. Probability of throwing a fastball at each pitch count. *Source*: Authors' calculations.

As a cursory check, we also investigate other measurable outcomes of pitch quality, including locational outcomes and runs given up. There is a requirement to throw to certain locations in order to be successful: the strike zone, defined by the MLB Rulebook as 'that area over home plate from the midpoint between a batter's shoulders and the top of the uniform pants—when the batter is in his stance and prepared to swing at a pitched ball—and a point just below the kneecap', (Major League Baseball 2023). We consider a measure of Pitch Location measured as the straight-line distance from the centre strike zone, calculated using the horizontal and vertical coordinates of the ball as it crosses home plate. We accompany this with a binary variable; Strike, which is equal to one if the pitch was swung at and missed or called as a strike by the umpire. We also use opposition score (or runs) as an outcome of pitcher performance. These measures come with the caveat that they are likely to be far noisier indicators of pitch quality than velocity. Opposition runs will of course be affected by the quality of the opposition batter(s), and even very small differences in location can determine success or failure, with ball and strike calls previously shown to be dependent on umpires (see Mills 2017).

4.2 Fatigue and task switching

To model the aggregate work done by a pitcher, we use their cumulative pitch count and its squared value. Our definition of task switching comes from pitchers having to bat and/or get on base during a game. More specifically, we identify pitches where the starting pitcher was batting and/or got on base in the previous (half) inning. The variable Prev AtBat is a dummy variable equal to one if a pitcher was batting in the previous half inning without getting on base. We also define Prev OnBase as a dummy variable equalling one if a pitcher managed to get on base during the previous half inning (regardless of how they got on base).[12] Figure 2 shows how the probability of batting in the previous inning (dashed line, RHS scale) and the probability of getting on base (dotted and dashed line, RHS scale) varies as a game progresses, along with the average velocity (solid line, LHS scale). Whether we can discern any causal association between these variables is the question of the analysis that follows.

[12] Defining task switching with half innings is key here. A pitcher pitching in the bottom of the (e.g.) sixth inning may have task switched in the top of the sixth, but a pitcher pitching in top of the sixth would have task switched in the bottom of the fifth inning.

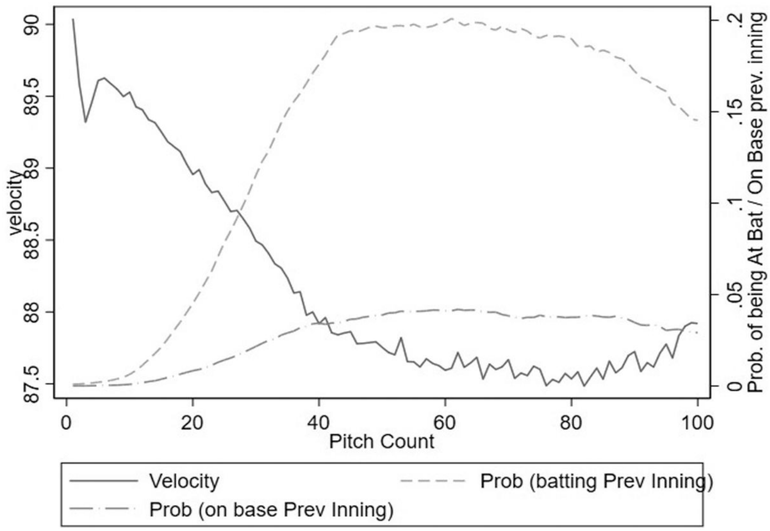

Figure 2. Average velocity and probability of batting and getting on base. *Source*: Authors' calculations.

Of course, an at-bat can result in several different outcomes, and what happens while at-bat is a likely determinant of subsequent pitching performance, rather than just batting per se. Certain outcomes are likely to involve a great deal more physical effort, such as sprinting to first base, while other outcomes may be less strenuous. As such, in Section 5.3, we offer an analysis breaking down the result of the at-bat into more granular events, namely hits, walks, strikeouts, groundouts, and flyouts, to examine differential effects by batting outcome.

4.3 Descriptive statistics

Table 1 shows the sample's descriptive statistics. Panel A is for all pitches thrown by starting pitchers, while Panel B is restricted to fastballs. The average point at which the starting pitcher is replaced is around pitch 89, with a maximum value of 134.

4.4 Estimation

For a given pitch, our model of velocity is as follows:

$$\begin{aligned} Velocity_{ig} = {} & \beta_0 + \beta_1 PitchCount_{ig} + \beta_2 PitchCount_{ig}^2 + \beta_3 PrevAtBat_{ig} + \beta_4 PrevAtBat \\ & * \ PitchCount_{ig} + \beta_5 PrevOnBase_{ig} + \beta_6 PrevOnBase \ * \ PitchCount_{ig} \\ & + \beta_7 PrevHalfInningLength_{ig} + \boldsymbol{\beta X} + PitcherFE + BatterFE + MonthFE \\ & + BallparkFE + SeasonFE + PitchTypeFE + \varepsilon_{ig} \end{aligned} \tag{1}$$

for pitcher i, in game g, such that we compare the performance of pitchers who have recently batted to those who have not batted in the most recent half inning. As discussed, we control for pitch count, along with its squared value, to capture any general fatiguing throughout a game. Prev At-Bat and Prev OnBase are the task switching variables, which we also interact with pitch count. We specifically include a control for the length of the previous half inning (i.e. when the opposition are pitching) to capture the effect of the pitchers most recent break from pitching, the aim being to disentangle the effect of switching tasks (batting) from just having a break from the main task. We include a set of fixed effects to

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev	Min	Max
Panel A: All pitches ($N = 1{,}291{,}074$)				
Outcomes				
Velocity (mph)[a]	88.11	5.88	40.90	101.90
Pitch location[b]	1.14	0.63	0.00	11.32
Strike (0,1)	0.46	0.50	0	1
Opposition Score	1.12	1.44	0	11
Explanatory variables				
Pitch Count	46.72	27.93	1	134
Prev At-Bat (0,1)	0.14	0.35	0	1
Prev On Base (0,1)	0.03	0.17	0	1
Length of Previous Half-Inning	15.77	6.27	1	51
Balls *(N of pre-pitch Balls in the count)*	0.88	0.97	0	4
Strikes *(N of pre-pitch Strikes in the count)*	0.89	0.82	0	2
Panel B: Fastballs ($N = 757{,}605$)				
Outcomes				
Velocity (mph)[c]	91.99	2.92	57.30	101.90
Pitch location [d]	1.06	0.55	0.00	9.69
Strike (0,1)	0.47	0.50	0	1
Opposition score	1.06	1.42	0	11
Explanatory variables				
Pitch Count	44.94	28.25	1	134
Prev At-Bat (0,1)	0.14	0.35	0	1
Prev On Base (0,1)	0.03	0.16	0	1
Length of Previous Half-Inning	15.83	6.31	1	51
Balls *(N of pre-pitch Balls in the count)*	0.92	1.01	0	4
Strikes *(N of pre-pitch Strikes in the count)*	0.82	0.82	0	2

Note: Number of observations for velocity and location differ.
Source: Authors' calculations.
[a] 1,285,793.
[b] 1,285,620.
[c] 757,433.
[d] 757,390.

capture any fixed unobserved differences by Pitcher, the opposing Batter, Month, Ballpark, Season, and Pitch Type.[13]

Within the vector **X**, we include the number of balls and strikes that the pitcher has thrown during the contemporaneous plate appearance (known as the count). These are important factors to consider since different counts are associated with more favourable outcomes for either the batter or the pitcher. When a pitcher is faced with allowing a walk (such as in a 3–0 count), pitchers are more likely to throw strikes down the centre, particularly fastballs. Though, when pitchers are in charge of the at-bat (0–2 count), they might throw slightly riskier pitches aimed at the extremities of the strike zone attempting to get the batter to swing, miss, and strikeout. To complete (1), ε_{ig} is a random error term. As outlined previously, our preferred specifications rely on fastball pitches.

In our context, there are two possible issues that could result in biased estimates. One is that there is non-random assignment of pitchers to leagues. Given that pitchers in the NL were required to bat, it might be that pitchers were hired not only on pitching ability but also on batting ability. This would be problematic for estimation if batting and pitching ability were correlated. However, we argue that is highly implausible. The pitcher is a

[13] Month Fixed Effects are potentially important in explaining temperature variations across the season, when in hotter months pitchers may fatigue quicker, and could also explain a general decline in performance over the course of a season. Pitch outcomes may also differ by ballparks, according to altitude, air pressure, wind conditions, etc.

highly specialized position, and they are hired to pitch. Batting, meanwhile, is purely a perfunctory duty for pitchers. Moreover, throughout high school and collegiate level baseball, pitchers would have faced some variant of the DH rule, protecting them from batting, and thus batting is a skill that pitchers rarely, if at all, practiced. Batting statistics also show pitchers to be poor hitters compared to other positions. In the 2019 season, pitchers had a 0.128 batting average with a 0.160 on-base percentage (OBP), while all other positions batted 0.256 with a 0.327 OPB (www.fangraphs.com).[14] Given all this, we believe the assumption of random assignment of pitchers to leagues is, on average, reasonable.[15]

The second concern is of within game selection, which presents a far more pressing threat to drawing conclusions about causality. More specifically, it is likely there is some unobserved component to pitcher fatigue, which affects when a team manager decides to pull their starting pitcher. Naturally, pitchers who are less fatigued (or simply having a good game) are less likely to be pulled, and as such, we are more likely to observe them batting (and getting on base), and subsequently pitching. Finigan, Mills, and Stone (2020) show that the decision to pull a starter is, on average, made at an efficient point in the game by managers in that pulling a starter does not significantly affect the probability of winning a game. Nevertheless, it remains true that the starting pitchers we observe batting deeper in games are those who are likely not as fatigued and/or having a better game than average. In short, this unobserved component would affect both our outcome variable (velocity; less fatigued pitchers can throw harder) and our treatment (task switching; less fatigued pitchers are more likely to be allowed to continue in the game and thus have a higher chance of task switching).

We address this possibility by employing a matching strategy, matching at-bats that are similar in terms of the probability that a pitcher is pulled based on observable characteristics about pitcher performance and current game scenario. The variables we match on resemble a subset of those described in Finigan, Mills, and Stone (2020), including recent pitcher performance, pitcher fatigue, upcoming pitcher-batter handedness matchups, and whether the opposition team has pulled their starter yet. Recent pitcher performance is modelled using the number of runs given up in the last three at-bats, and the number of walks plus hits allowed in the last three at-bats. Pitcher fatigue is modelled using average fastball velocity over the last three at-bats. Meanwhile, same handed pitcher-batter matchups are thought to be advantageous for the pitcher. Given that upcoming batters are known to team managers, we model this influence using the proportion of same handed matchups in the next three at-bats. We also control for the current scoreline (measured as the difference between pitching team and batting team runs), and whether the opposition team still has their starter in the game. Table 2 presents the results from a simple probit model to demonstrate that the variables correctly predict starting pitchers being pulled (i.e. enter a regression with the anticipated sign). The outcome equals 1 if a starting pitcher is pulled at the end of a current at-bat, 0 otherwise.

In Fig. 3, we plot the predicted probabilities based off the model in Table 2, across both at-bats where pitchers were batting in the previous half inning (dashed line) and pitchers who were not batting in the previous half inning (solid line). The probability of being pulled at any point in the game is understandably low as this is a relatively rare event compared to the number of at-bats.

We proceed to match on at-bats using CEM, described in Iacus, King, and Porro (2012). The simple aim of any matching technique is to achieve better balance between treated and control groups by pruning observations where there is poor overlap. In our case, treated

[14] Batting Average is calculated by dividing a player's total hits by his total at-bats, producing a statistic between 0.000 and 1.000 (reported to 3dp). OBP is a measure of how frequently a batter reaches base per plate appearance.

[15] Shohei Ohtani is, of course, an exception to this. However, as any baseball fan knows, Ohtani is an exception to just about any usual rule for baseball players. Nevertheless, Ohtani plays in the American League, despite being an excellent pitcher and hitter, and did not bat on days he pitched in our data.

Table 2. Probit model to predict starting pitcher replacement.

Variable	Marginal effect
Proportion of same handed match ups in next three at-bats	−0.026***
Runs given up in last three at-bats	0.002***
Walks plus hits given up in last three at-bats	0.005***
Fastball speed in last three at-bats	−0.002***
Scoreline	−0.007***
Opposition starter still in game	−0.066***
N (at-bats)	277,640

Note: Outcome is whether the pitcher is pulled at the end of an at-bat. Unit of observation is the at-bat level.
Source: Authors' calculations.
*** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

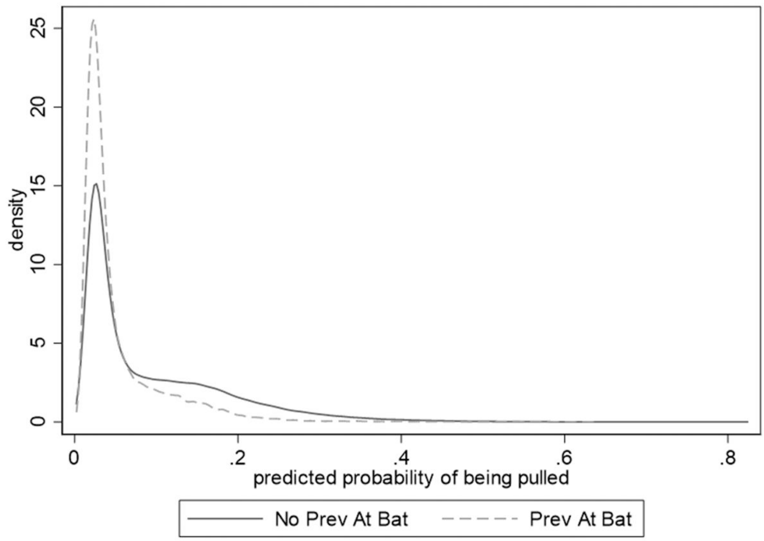

Figure 3. Predicted probabilities of being pulled. *Source*: Authors' calculations.

observations are pitchers who have recently task switched. Many matching techniques however, including the widely used propensity score matching (PSM), have been shown to be problematic in that they can actually increase imbalance (King and Nielsen 2019). In contrast, exact matching would require that each treated unit is matched to a control unit with identical pre-treatment covariates, such that perfect balance is achieved. While this is desirable, it is often not feasible due to the curse of dimensionality (Blackwell et al. 2009), even with large data such as ours.

As such, CEM works by coarsening these covariates (where coarsening means creating bins, or strata) and then finding exact matches within the coarsened data, pruning any unmatched observations. Matched observations are then given a weight, which can then be used in a re- weighted OLS regression. In many empirical applications, the researcher can coarsen the data into pre-specified strata that might occur naturally in the data. In our case, it is less clear whether any naturally occurring strata occur in our covariates, with the exception of the proportion of same handed match ups in the next three at-bats (4 strata) and whether the opposition starter is still in the game (binary, i.e. 2 strata). Thus, we allow the statistical package's in-built routine to determine the coarsening for the remaining variables.[16] Across the sample of starting pitchers, there are a total of 332,397 at-bats, 14,471 of which end in a pitcher being pulled, which means the pitcher continues in the remaining 317,926. CEM matches on 14,433 at-bats where the pitcher is pulled, and 284,776 at-bats where the pitcher is allowed to continue. The remaining 33,188 at-bats are pruned.

5. Results

5.1 Baseline estimates

We first present results from the velocity regressions in Table 3. Higher pitch counts are associated with declining velocity, albeit at a declining rate. On average, each pitch loses between 0.005 and 0.012 mph in velocity, varying across specifications. Given that our estimates include fixed effects for individual pitchers, the decline in velocity is likely capturing the gradual deterioration in performance due to fatigue as the game progresses.

Of note are the positive and significant coefficients on Prev At-Bat and Prev On Base, indicating that pitchers who were batting and got on base in the previous (half) inning, on average, throw higher velocity pitches. This is particularly true when restricting the samples to just fastballs, with the average fastball velocity increasing by between 0.099 and 0.115 mph after only batting and increasing by between 0.153 and 0.225 mph if the pitcher got on base. The magnitude of the effect is far smaller when considering all pitches, though we note that expectations about the direction of fatigue-related velocity changes on off-speed pitches are somewhat ambiguous. While the sizes of these point estimates are not especially large, velocity is a noisy indicator with various potential influences. After getting on base, the interaction with pitch count is negative indicating that the initial positive effect wears off as the inning progresses.

There are two prominent reasons that might explain the increased velocity after task switching. First, task switching gives a pitcher an opportunity to keep warm between innings rather than sitting on the side-lines waiting for their next pitching stint. In between innings, without batting, pitchers might start to stiffen-up. Instead, by batting, pitchers can instead keep warm ahead of their next pitching stint. Second, and somewhat paradoxically, fatigue from batting may affect a pitcher's grip in such a way that velocity, particularly for off-speed pitches, increases. Recent fatigue or gripping a bat might impede a pitcher's ability to grip the baseball as tightly or precisely when pitching shortly thereafter, which is key to slowing down off-speed pitches. As a result, subsequent off-speed pitches may be thrown faster and straighter than expected, reducing their effectiveness. Given the result is particularly apparent with fastballs, this tends to provide stronger evidence for the 'staying loose' effect.

It is worth noting that Bond and Poskanser (2023) also uncover a positive effect of batting on subsequent pitching performance. Results in Table 3 show that this extends to an isolated underlying measure of pitcher performance, and not potentially entangled with batter and fielder ability. Our results also suggest that the performance impacts may be physical in nature, rather than related to mental switching as proposed by this past work. This is particularly supported by the larger effect estimated for getting on base. Reaching base is an unusual event for a pitcher, who has the potential to: (1) stay even warmer by moving around, (2) suffer fatigue, and/or (3) obtain increased adrenaline from the excitement of reaching base. We test this last possibility below by using particularly rare hitting events in the next section. It is also telling that longer previous half innings (i.e. longer rest periods) enter with a negative effect on velocity. This adds an additional layer of confidence that the positive effects of task switching are driven by the act of batting/getting on base, rather than just an opportunity to sit on the sidelines.

[16] We use the Stata command *cem* to implement Coarsened Exact Matching (Blackwell et al. 2009).

Table 3. Effects of task switching on velocity.

	(1)	(2)	(3)	(4)
Variables	OLS	OLS with CEM	OLS	OLS with CEM
	Velocity (mph)			
Pitch count	−0.004***	−0.010***	−0.004***	−0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
Pitch count squared/1000	−0.004	0.041***	−0.004	0.055***
	(0.002)	(0.003)	(0.002)	(0.003)
Prev At-Bat	0.070***	0.032**	0.115***	0.099***
	(0.014)	(0.014)	(0.013)	(0.013)
Prev At-Bat * Pitched count	−0.001***	0.000*	−0.001***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Prev On Base	0.075**	0.167***	0.153***	0.225***
	(0.029)	(0.029)	(0.028)	(0.027)
Prev On Base * Pitched count	−0.000	−0.002***	−0.000	−0.002***
	(0.001)	(0.000)	(0.000)	(0.000)
Balls in count	0.038***	0.041***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Strikes in count	0.389***	0.377***	0.435***	0.427***
	(0.002)	(0.002)	(0.002)	(0.002)
Prev half inning length	−0.006***	−0.005***	−0.007***	−0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	79.218***	79.474***	82.562***	82.916***
	(0.226)	(0.238)	(0.208)	(0.226)
Fastballs only	No	No	Yes	Yes
Observations	1,228,609	1,117,912	720,046	639,241
R-squared	0.897	0.897	0.775	0.778

Note: Each model includes Pitcher, Batter, Month, Season, Ballpark, and Pitch Type Fixed Effects. Standard errors in parentheses.
Source: Authors' calculations.
*** $P < .01$, ** $P < .05$, * $P < .1$.

5.2 Heterogeneity of at-bats

It is reasonable that a pitcher's batting outcomes themselves may affect subsequent pitching outcomes. To this point, our definitions of task switching, Prev At-Bat, and Prev On Base have assumed them to be just binary events. However, this definition masks a large degree of heterogeneity with regards to what a batter does whilst at-bat or in the process of getting on base. Most importantly, this analysis also helps us to disentangle a number of competing explanations regarding the mechanism behind the positive effect of task switching.

For example, a batter may swing and miss at three strikes and get an out, they could be awarded a walk to first base without swinging at all, they could hit a pitch into play and are required sprint to first base, and so on. These events are likely to induce different physiological and mental responses. As such, we continue by exploring the importance of what happens at-bat, and if the pitcher does make it to base, whether the way that getting on base happens (walk, hit, etc.) matters to our coefficient estimates. We focus on six categories of batting outcomes: hits (with one model for singles and one for doubles and triples), home runs, walks and hit by pitches, strikeouts, groundouts, and flyouts.[17] We also estimate a model estimating the effect for any type of out if this out was the third out in the previous half inning. Each involves a different amount of physical exertion. For example, we might expect batters to sprint for a double, but very little (or no) sprinting might be

[17] There are numerous possible outcomes following a plate appearance. However, some are so rare that we would gain very little by examining them. These outcomes are a combination of the most common and interesting events to examine. An extra base hit is defined as any hit that is not a single (doubles, triples and home runs).

Table 4. Previous at-bat event.

	(1) OLS	(2) OLS with CEM	(3) OLS	(4) OLS with CEM
Variables	Velocity (mph)			
Panel A: singles (n = 1,237/19,464)				
Prev single	−0.029**	−0.005	0.022*	0.020
	(0.014)	(0.014)	(0.014)	(0.013)
Panel B: doubles and triples (n = 215/3,287)				
Prev double/triple	0.112***	0.107***	0.078**	0.068**
	(0.033)	(0.032)	(0.032)	(0.031)
Panel C: home runs (n = 61/952)				
Prev home run	0.143**	0.231***	0.242***	0.252***
	(0.062)	(0.059)	(0.057)	(0.056)
Panel D: walks or hit by pitch (n = 438/6,918)				
Prev walk/hit by pitch	0.034	0.065***	0.062***	0.036*
	(0.023)	(0.022)	(0.022)	(0.021)
Panel E: strikeouts (n = 5,774/89,816)				
Prev strikeout	0.022***	0.041***	0.037***	0.058***
	(0.007)	(0.007)	(0.007)	(0.007)
Panel F: groundouts (n = 3,473/54,691)				
Prev groundout	0.030***	0.056***	0.042***	0.076***
	(0.009)	(0.009)	(0.008)	(0.008)
Panel G: flyouts (n = 931/14,400)				
Prev flyout	0.091***	0.071***	0.091***	0.063***
	(0.016)	(0.016)	(0.016)	(0.015)
Panel H: third out in inning (n = 4,102/64,221)				
Prev third Out	0.032***	0.054***	0.054***	0.091***
	(0.008)	(0.008)	(0.007)	(0.008)
Fastballs only	No	No	Yes	Yes

Note: Each model controls for Pitch Count and its square, the number of pre-pitch Balls and strikes in the count, the previous half inning pitch count, along with Pitcher, Batter, Month, Season, Ballpark, and Pitch Type Fixed Effects. The number of observations listed in each panel is first the frequency of each event (e.g. how many times a pitcher, when batting, hit a single), followed by the number of pitches they throw in the next half inning after that event (e.g. the number of pitches thrown in the half inning after a single). Standard errors in parentheses.
Source: Authors' calculations.
*** $P < .01$, ** $P < .05$, * $P < .1$.

involved after hitting a home run or striking out. Moreover, rare and unexpected events such as hitting a home run might be associated with a positive mental/adrenaline response, which may impact subsequent pitching performance (particularly with respect to velocity increases). Results of these additional models are shown in Table 4.

While the results square with the positive coefficients of Prev At-Bat and Prev On Base from Table 3, we can also see heterogeneity across the different outcomes of an at-bat. Most notably, home runs result in a much larger increase in subsequent pitching velocity than other batting outcomes and drives some of the effect of Prev At-Bat. Although the frequency of home runs hit by pitchers is very small, they are associated with an increase in velocity of between 0.242 and 0.252 mph for fastballs. There are also statistically significant and positive effects, though smaller in magnitude, for walks/hit-by-pitches, doubles and triples, and singles. Walks (despite what their name would suggest), hit-by-pitches, singles, doubles, and triples all require pitchers to run the bases while other players bat, creating an additional task switching event. Alternatively, similarly to outs, home runs only require the pitcher round the bases on their own and return to the bench. Given this, the results are consistent with batting in general being associated with positive effects, regardless of any subsequent running bases that follows.

Table 5. Other pitching outcomes.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Pitch location		Strike (0,1)		Opposition score	
Pitch count	0.000	0.000***	−0.000***	−0.001***	0.068***	0.067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pitch count squared/1000	0.001	−0.002*	0.003***	0.005***	−0.371***	−0.364***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Prev At-Bat	−0.005***	−0.002	0.002*	0.003*	−0.247***	−0.253***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)	(0.006)
Prev On Base	−0.013***	−0.012***	0.008***	0.014***	−0.302***	−0.335***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.009)	(0.011)
Prev half inning length	0.000**	0.000	0.000	0.000	−0.001**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.094***	1.003***	0.693***	0.654***	−0.528***	−0.561**
	(0.076)	(0.088)	(0.062)	(0.080)	(0.197)	(0.253)
Fastballs only	No	Yes	No	Yes	No	Yes
Observations	1,117,845	639,201	1,118,871	639,346	1,118,871	639,346
R-squared	0.073	0.050	0.022	0.025	0.214	0.218

Note: Each model includes Pitcher, Batter, Month, Season, Ballpark, and Pitch Type Fixed Effects, and balls and strikes in the count. Each model is estimated using OLS and includes CEM weights. Standard errors in parentheses.
Source: Authors' calculations.
*** $P < .01$, ** $P < .05$, * $P < .1$.

The sizeable effect of home runs also introduces another possibility: given the rarity of home runs, pitchers seem to receive an additional adrenaline response from this strong success while at the plate. As a result, their subsequent pitching performance, at least as measured by velocity, improves substantially. This effect is not dependent on the type of out, with consistent coefficient effects across strikeouts (no running), groundouts (more sprinting), and flyouts (more jogging). Given that sprints are also usually required when a pitcher grounds out, the effect of baserunning is unlikely to be related to fatigue. Although this may suggest that additional preparation time on the bench is beneficial to pitchers when returning to the prior task, the effects of making the final out in an inning violate this.

This result is somewhat in contrast to recent work from Bond and Poskanzer (2023), which suggests that there are positive mental effects associated directly with failing in the non-standard task (batting). Rather, long spells on the sidelines appear to impede a pitcher's ability to throw (as measured by velocity) and the act of batting allows the pitcher to stay in a better physical condition. While we cannot rule out fatigue effects from running bases, on average our results suggest it is still beneficial to not sit on the bench, as both positive and negative batting outcomes are associated with positive pitching performance effects. Moreover, rare events such as home runs appear to induce an additional adrenaline response that can further improve pitcher performance. This would not be apparent without identifying the separate (very positive) effect of hitting a home run relative to other positive outcomes that require running the bases. As such, this is pivotal in properly understanding how task switching impacts worker performance, particularly in this context.

5.3 Other outcomes

Next, we focus on other indicators of pitching performance, presented in Table 5: distance from the strike zone centre, throwing a strike, and opposition scoring. All models are estimated with OLS including CEM weights. From column (1), higher pitch counts are associated with throwing fastball pitches further away from the centre of the strike zone, which is also reflected in a reduction in fastball strike probability associated with higher pitch counts in column (4). This is countered by the effects of previously getting on base. Pitches thrown in the inning immediately after getting on base are closer to the centre of the strike zone (columns 1 and 2) but these are more likely to be strikes than in other innings (columns 3 and 4). This is suggestive of improved pitching performance following getting on base.

Columns (5) and (6) examine runs given up by the pitcher. The pitcher's objective is to minimize opposition runs. Countering the increased runs given up as the game progresses is the negative effect of batting and getting on base. Results suggest that pitchers give up between 0.247 and 0.253 fewer runs when pitching in the inning immediately after their at-bats, or between 0.302 and 0.335 fewer runs after getting on base (likely driven by home runs, as shown in Table 4). These are rather large effects, and as we noted earlier, likely include various other influences such as fielding quality and luck. Nevertheless, the net results from increased velocity and strike rates are expected to be a nontrivial contributor to this expected run decrease.

6. Discussion and conclusion

Attempting to quantify the effects of task switching on short term (in our setting, that translates to within game) productivity is not straightforward, not least due to difficulties in defining and comparing performance. Using play-by-play data from three seasons of MLB, we overcome this difficulty and have shown task switching in the form of batting in the previous (half) inning results in some beneficial effects on pitching performance. In our preferred specifications which rely on fastballs and use CEM to account for pitcher replacement, fastball velocity increases by up to 0.225 mph on average after reaching base. Substantial heterogeneity exists with this effect, with the largest effect on velocity occurring after a pitcher hits a home run, increasing velocity as much as 0.252 mph.

At first, this positive effect may seem counterintuitive under the prior assumption that switching between batting and pitching may incur a switching cost and place additional physical demands on the pitcher. However, we are not the first empirical paper to find evidence that some task switching can be beneficial to performance. Namely, Singh (2014) found that physicians' performance improved for up to about four patients per hour for each additional patient. Only after this point did the extra demands from task switching hinder performance. Moreover, if we assume that having to switch tasks within games creates a more challenging working environment, then according to Hommel et al. (2012) there is both behavioural and neuroscientific evidence suggesting that in the face of increased difficulty of tasks, subjects increase their effort to compensate for and overcome that challenge. Srna, Schrift, and Zauberman (2018) have also showed this phenomenon experimentally. Most recently in the same baseball context, Bond and Poskanser (2023) find positive effects of task switching for MLB pitchers.

As for how we can explain these results in a baseball setting, it is possible that the switch between pitching and batting offers pitchers an opportunity to recuperate both mentally and physically. For example, batting could act as a distraction from the core task. A pitcher between innings but not batting would have more time to ruminate on any previous mistakes, which might distract their mental focus and diminish their subsequent pitching performance. Batting could simply reduce mental stress associated with pitching. Our results also strongly point to there being a physical mechanism at play; if pitchers begin to stiffen up whilst between innings, then batting may help pitchers 'keep warm' between innings, loosening their joints and muscles in preparation for pitching. Indeed, longer spells on the sideline are associated with worse performance, but this is negated by batting. Also, there tends to be a much larger positive effect when unexpected positive events happen when the pitcher bats, suggesting adrenaline or excitement responses that increase physical performance (at least in the short term) in the subsequent inning. This result implies that explanations based on prior work claiming to show stronger effects when pitchers fail at this task should be revisited. Rather than failure improving performance, in baseball, failure in the alternative task removes any requirement to do additional task-switching to a third task.

As for how generalizable these results are to other sports and industries, there is certainly scope to abstract away from baseball. Cricket would provide an interesting sporting parallel. While there is nothing analogous to the Designated Hitter rule in cricket, specialist bowlers must appear in the batting order (although they are usually last). Our results suggest that by not having a rule analogous to the Designated Hitter rule, bowlers in cricket might benefit from having to take part in the offensive part of the game. While other sports, such as football (soccer) and rugby, do involve players carrying out different roles (i.e. attacking and defending), the sequential nature of these tasks is not as defined as in baseball. More generally, a scenario where temporarily moving away from one's main task would fit the same story. In particular, workers in industries that are required to carry out physical (and possibly repetitive) yet precise tasks might indeed benefit from task switching as long as they are not asked to continuously switch to additional tasks. Construction work is possibly the most analogous.

This work also leaves many interesting questions open for future research. Now that MLB has moved to a universal DH rule, one may be interested in looking at how this has altered the performance of pitchers and the behaviour of associated management decisions. Moreover, future research could examine what other events might lead to improved pitcher performance, including the role of teammate and opposition actions.

Supplementary material

Supplementary material is available at the *Oxford Economics Papers Journal* online. These include the data and replication files. The data used in this article are also publicly available from Baseball Savant (https://baseballsavant.mlb.com/).

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