# Technological Change and Obsolete Skills: Evidence from Men's Professional Tennis\*

Ian Fillmore<sup>†</sup> Jonathan D. Hall<sup>‡</sup>

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<sup>&</sup>lt;sup>†</sup>Washington University in St. Louis, ianfillmore@wustl.edu.

<sup>&</sup>lt;sup>‡</sup>University of Toronto, jonathan.hall@utoronto.ca.

#### **Abstract**

Technological innovation can raise the value of some, sometimes new, skills while making previous skills less valuable or even obsolete. We study the short- and long-run effects of such skill-altering technological change in the context of men's professional tennis, which was unexpectedly transformed by the invention of composite racquets in the late 1970s. We explore the consequences of this innovation on player productivity, entry and exit, and career performance. We find that young players benefited at the expense of older players and that the disruptive effects of the new racquets persisted over two to four generations.

#### 1 Introduction

The last two centuries have witnessed an enormous amount of technological innovation, and this is widely viewed as the primary source of long run economic growth and improvements in well-being. Yet, as Acemoglu (2002) points out, innovation does not help all workers: "in nineteenth-century Britain, skilled artisans destroyed weaving, spinning, and threshing machines during the Luddite and Captain Swing riots, in the belief that the new machines would make their skills redundant. They were right: the artisan shop was replaced by the factory and later by interchangeable parts and the assembly line." New technologies disrupt the labor market as they raise the value of some, sometimes new, skills while making previous skills less valuable or even obsolete. We call this phenomenon skill-altering technological change. We present evidence that skill-altering technological change helps young workers—who are better able to adapt their skills to the new technology—at the expense of older workers—who have already made investments based on the now-outdated technology.

Consider three occupations affected by skill-altering technological change: painters in the 19th century, farmers in the mid-20th century, and architects in the 1980s. First, painters were confronted with the invention of photography in the mid-19th century. With the arrival of an inexpensive alternative for capturing realistic portraits, painters began looking for ways to differentiate themselves, leading to the rise of impressionism which emerged just as the photograph was becoming

<sup>&</sup>lt;sup>1</sup>We refer to this change as skill-altering, rather than skill-biased, because once we are considering a basket of skills (rather than a single dimension of skill), whether or not a given technological change is skill-biased depends on the current (implicit) prices for those skills in the market. That is, whether a given basket of skills represents "more skill" than another basket ultimately depends on the current prices for those skills in the market, and thus whether a technological change that raises the value of one basket of skills relative to another is skill-biased depends on which basket was more valuable to begin with.

popular. Moreover, photography found its way into the artistic process: "... artists working in all media began using the camera as an intriguing toy, as a means of providing images to be used as studies for final works, and as another way of observing the world" (Easton, 2012). As a second example, it is difficult to overstate the extent to which the rise of tractors in the 20th century changed farming. While tractors made almost any farmer more productive, they also had subtler effects on optimal farming practices. With a tractor on the farm, the old traditional approach to farming that relied on work animals gave way to more modern farming techniques that rely on machines. Finally, MacDonald and Weisbach (2004) point to the development of computer-aided drafting in architecture. This new software had the effect of devaluing drafting and engineering skills relative to artistic skills in designing new buildings. Older architects found the transition difficult, with the New York Times reporting that "as young architects plunge into the high-tech tide, older colleagues wade in gingerly."<sup>2</sup> In all three examples, the new technology altered the relative value of different skills. In the cases of farmers and architects, the average age in those occupations temporarily fell, relative to the general population, just after the new technology arrived (see Figure 1). Indeed, we might expect just such a dip in age if younger workers are better able to adapt and take advantage of the new technology.

Figure 1 is suggestive, but far from conclusive. Ideally, we would obtain panel data on multiple cohorts of workers in the same occupation before and after the innovation, but such data is hard to come by. Often it is unclear how much an innovation was anticipated, and the arrival of the new technology is difficult to date. The innovation often develops over the course of several years or even

<sup>&</sup>lt;sup>2</sup>Dunlap, David. "Computer design: Castles, and planetariums, in the air." *New York Times.* 11 March 1999.

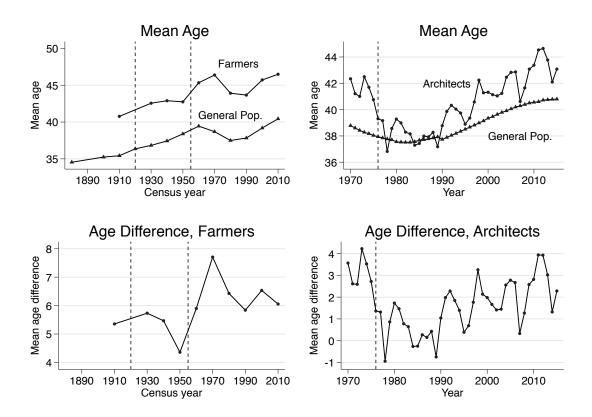


Figure 1: The rise of tractors and the arrival of architectural software

*Source:* United States Current Population Survey (Flood et al., 2017), United States Census, and American Community Survey (Ruggles et al., 2018)

Notes: Data on farmers come from the Census through 2000 and the five-year ACS (2008-2012) for 2010. Data on architects come from the March CPS prior to 1976, and from the basic monthly CPS thereafter. Samples restricted to ages 18-64. Tractors per farm rose from only 1 in 26 in 1920 to nearly 1 to 1 in 1955 (see Table 2 of Binswanger (1986)). We date the arrival of architectural software to around 1976. The first computer-aided drafting programs were developed in the early 1960s, but didn't start being used widely until much later. As late as 1977, firms could claim to be among the first in their state to be using computer-aided design (Zahler, Miriam. "Architects turn to computers for drafting and design work." *Crain's Detroit Business*. 13 October 1986).

decades, thereby making it difficult to disentangle the effects of the innovation from other factors that are changing over the same period. Workers' careers are long, so it would take many decades to observe the long run effects of the innovation, and wages depend on many factors which may also be changing over time.

To address these challenges, we exploit a major innovation in men's professional tennis—the introduction of composite racquets in the late 1970s and early 1980s. These new racquets drastically changed the way the game was played, and in particular, increased the relative importance of hitting with spin and power. There are four reasons this episode in men's professional tennis is a useful setting to study the effects of skill-altering technological change on workers. First, we have detailed panel data on multiple cohorts of individual workers (players), allowing us to track the long run impacts of the innovation. Second, the new technology arrived suddenly and rather unexpectedly and was also universally adopted within a few short years (see Figure 2). This is valuable because the timing of the innovation is obvious, the quickness of the transition reduces the concern that other economic shocks are driving the results, and this particular innovation was specific to tennis. Third, tennis careers are relatively short—six years on average and rarely more than 15 years—which allows us to follow multiple cohorts of players over their entire careers. Fourth, since we can observe the performance of a player without worrying about the effects of teammates, professional tennis offers us unusually clean measures of worker productivity.

We start with a simple overlapping generations model in the spirit of Mac-Donald and Weisbach (2004). We extend their model by allowing players to endogenously choose how much to invest in two different skills, spin/power and control, and by having their performance depend both on their skills and the relative weights the current racquet technology puts on each skill. We model the introduction of the composite racquets as an increase in total factor productivity, and, more importantly, a change in the relative weights of the two skills. As in Autor et al. (2003), we use our model to make testable predictions about the effects of skill-altering technological change and test these predictions empirically. We find that the introduction of the new composite racquets temporarily helped younger players at the expense of older players, reduced the rank correlation in player quality over time, and increased exit rates of older players relative to younger players. We find that these effects persisted for two to four generations of players.

This paper contributes to the literature on skills and technological change, as well as the more recent literature on the effects of labor demand shocks on workers. Within this literature we build most closely on two papers which measure how the introduction of new technology affects workers. Akerman et al. (2015) use the exogenous roll-out of broadband internet in Norway, and Gaggl and Wright (2017) use variation induced by an unexpected UK tax credit for small firms which invested in information and communication technology. We build on their work by introducing a model of skill-altering technological change and using panel data on individual workers to trace out the effect of a technological innovation on workers over time, as well as to examine how this effect differs based on worker experience.

Our paper also builds on a long literature using sports as a laboratory for investigating broader economic phenomenon.<sup>3</sup> Within this literature, we build most closely on Gannaway et al. (2014) which investigates the effects of the introduction

<sup>&</sup>lt;sup>3</sup>For recent examples, see Coffey and Maloney (2010), Brown (2011), Pope and Schweitzer (2011), Genakos and Pagliero (2012), Abramitzky et al. (2012), Kleven et al. (2013), Croxson and Reade (2014), Chen et al. (2016), Arcidiacono et al. (2017), and Sandberg (2017).

of the three-point line in NBA basketball. They find that the equilibrium effect of the three-point line was to increase the productivity of players who shoot closer to the basket (forwards and centers) and that the demand for height in the NBA rose as a result. That is, the technology altered the demand for different types of players. Our paper builds on this result by exploring the dynamics of how a new technology affects players with different amounts of experience over time.

The structure of the paper is as follows. We explain the nature of the technological shock in men's tennis in Section 2, and introduce our model in Section 3. In Section 4 we use this model to understand how players are affected by the introduction of a skill-altering technology. Next we introduce our data in Section 5 and describe how we estimate player quality using this data in Section 6. We test the predictions of the model in Section 7. In Section 8 we conclude.

# 2 Background

Up until the mid-1970s, tennis racquets were made almost exclusively with wood. Although alternative materials were tried, such as the steel Wilson T-2000 which was used by a few players, the vast majority of players continued to play with wood racquets. In 1976, Howard Head introduced the Prince Classic tennis racquet—the first "over-sized" racquet to gain widespread appeal. The racquet had a larger string bed and sweet spot which made it easier for players to make good contact with the ball and generate more power and spin. Unfortunately, the aluminum Prince Classic achieved these gains at the expense of stiffness and control, making the racquet unacceptable for professional players. Racquet makers quickly found a solution—they developed methods for constructing the racquet frame out of a

composite material consisting of a mixture of carbon fibers and resin. Composite frames allowed both a larger string bed and a stiff frame, giving players more power *and* control. The first composite racquet to be used by professionals, the Prince Pro, hit the market in 1978, and composite racquets quickly replaced wood racquets as professional players found that their familiar wood racquets were no match for the combination of power and control afforded by the new composite racquets. By 1983 the share of wooden racquets accounted for only 25 percent of the high-priced racquet market,<sup>4</sup> and by 1984, composite racquets had taken over the tour. Figure 2 illustrates this transition by looking at the racquets used to win each of the four Grand Slam tournaments over time.<sup>5</sup>

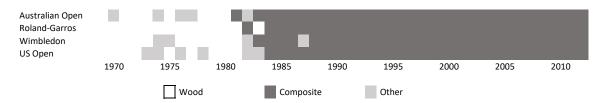


Figure 2: Racquet type used to win each Grand Slam over time

Source: Les Raquettes de Legende (2012)

*Notes:* Other racquets include a variety of racquet types including metal racquets as well as wood racquets with graphite inlays.

The advent of composite tennis racquets significantly changed the way men's professional tennis was played. When tennis players strike the ball, they often try to impart topspin. Topspin causes the ball to rise over the net and then dip downward, helping it to stay in the court. Moreover, a ball hit with topspin "jumps" off the court, making it more difficult for the opponent to return. All else equal, the more topspin a player can impart, the harder he can hit the ball and still keep

<sup>&</sup>lt;sup>4</sup>Armstrong, Scott. "Technology Tugs at Tennis Traditions." *Christian Science Monitor.* 6 September 1983.

<sup>&</sup>lt;sup>5</sup>Figure 2 represents the most comprehensive data we could find on the racquets used by individual players.

it in play and the more difficult it will be for his opponent to hit the ball back. Wood racquets only allowed players to impart a modest amount of topspin, which limited the speed with which they could hit the ball. In contrast, composite tennis racquets greatly increased the amount of topspin a player could impart, opening up the possibility for players to hit more powerful and penetrating shots. Physicist Rod Cross (2006) provides a numerical example to illustrate why the composite racquet had such a large effect on how the game was played.

When a ball bounces off the court it acquires topspin, even if it had no spin before it hit the court. In fact, it spins faster than most players can generate themselves when they hit a topspin return. In order to return the ball with topspin, a player needs to swing the racquet both forwards and upwards and fast enough to reverse the rotation of the spinning ball. . . .

Suppose, for example, that the ball spins at 3,000 rpm (50 revolutions/sec) after it bounces off the court. That is a typical amount of spin when a ball hits the court at around 30 or 40 mph. Returned with a wood racquet, a player won't be able to swing up at a very steep angle without clipping the frame. He will still be able to reverse the spin, but he will get only 200 rpm or so of topspin by swinging the racquet upward fairly rapidly at about 20 degrees to the horizontal. A change in spin from 3,000 rpm backwards to 200 rpm forwards is a change of 3,200 rpm, which is a relatively big change, but it is only enough to return the ball with a small amount of topspin.

Now suppose the player switches to a 10-inch-wide racquet and swings up at 30 degrees to the ball. The player can do that and can also tilt the racquet head forward by about 5 degrees, with even less risk of clipping the frame than with a 9-inch-wide wood racquet being swung at 20 degrees with the head perpendicular to the ground. In this way, the player will be able to change the spin by about 4,000 rpm instead of 3,200 rpm, with the result that the spin changes from 3,000 rpm of backspin to 1,000 rpm of topspin. The result is therefore a factor of five increase, from 200 rpm to 1,000 rpm, in the amount of topspin.

Although composite racquets allowed players to generate much more topspin and power, taking full advantage of this potential required significant changes in the players' strokes and playing styles. Older players in particular, who had invested years into learning to play with a wood racquet, faced the daunting challenge of adjusting to the composite racquets. Players began altering their stances and swings to generate more topspin and power. They rotated their grips to generate more spin as well as to help them return balls that were bouncing higher because of the increased topspin of their opponents. These seemingly subtle changes in technique and strategy resulted in a much more physical and faster-paced game. As Cross puts it,

The modern game of tennis is played at a furious pace compared with the old days when everyone used wood racquets. Just watch old film from the 1950s and you will see that the game is vastly different. Ken Rosewall and Lew Hoad barely broke into a sweat. Today's game has players grunting and screaming on every shot, calling for the towel every third shot, and launching themselves off the court with the ferocity of their strokes.

From the perspective of an economist, men's professional tennis experienced a technological shock in the late 1970s and early 1980s, and the new technology required a different skill set than the prior technology. That is, the new racquets represented a skill-altering technological change. Although players quickly adopted the new technology, it took some time for them to acquire the new skills that were necessary in order to use that technology most effectively. Our data allow us to explore the short and long run effects of this skill-altering technological change.

#### 3 Model

## 3.1 Player skills and quality

To guide our empirical analysis later in the paper, we develop a model of skill-altering technological change. The model is a simple overlapping generations model in the spirit of MacDonald and Weisbach (2004). Each cohort consists of a mass one of players, each of whom live for three periods. We index periods with t and a player's age with a. Let  $s_i$  denote the period player i is "born," so that a player's age in period t is just  $a_i(t) = t - s_i + 1$ . A player's performance at age a depends both on his skills and how these skills combine with the current racquet technology. Let  $\{x_{ia}, y_{ia}\}$  denote player i's skills at age a (these skills might be thought of as being control and power). A racquet technology r consists of the pair  $(A_r, \lambda_r)$ , and a player's quality  $q_{iar}$  using racquet technology r is given by

$$q_{iar} = A_r x_{ia}^{\lambda_r} y_{ia}^{1-\lambda_r}$$

so that

$$\log q_{iar} = \log A_r + \lambda_r \log x_{ia} + (1 - \lambda_r) \log y_{ia}.$$

Changes in the parameters  $A_r$  and  $\lambda_r$  affect players differently. The parameter  $\lambda_r \in (0,1)$  controls the relative importance of skill x in using that racquet. A technology shock that decreases (increases)  $\lambda_r$  will help players who have relatively more (less) of skill y. Increases in  $A_r$  is an increase in total factor productivity and increases quality for every player. However, player performance is zero-sum—every win for one player corresponds to a loss for another player—and, under the assumptions we make in Section 6, an increase in  $A_r$  for all players will not affect the probability that one player defeats another.

#### 3.2 Evolution of skill

Players choose an optimal mix of skill investment, and their skills evolve over time. Player i is born in period  $s_i$  with a common skill vector  $\{x_0, y_0\} \in \mathcal{R}^2_+$ . At age a, he selects the optimal technology for his skill composition and improves by  $(\alpha_a + \epsilon_{ia}) \left(\lambda_r^2 + (1 - \lambda_r)^2\right)^{-1/2}$  units in the  $\log x$ - $\log y$  plane, where the shock  $\epsilon_{ia}$  is mean zero and iid with distribution F and  $\left(\lambda_r^2 + (1 - \lambda_r)^2\right)^{-1/2}$  serves as a normalizing constant. A player chooses the optimal direction of improvement in  $\log x$ - $\log y$  space, which amounts to setting the direction of improvement perpendicular to the isoquant of the racquet technology he is using. Note that, although players choose the *direction* of investment in skills, the amount of improvement

<sup>&</sup>lt;sup>6</sup>See Appendix Section A.7 for a discussion about allowing for heterogeneous initial skills.foot <sup>7</sup>It is worth noting that our model does not allow for skills to depreciate. Earlier versions of the paper had this feature, but it added complexity without adding any additional insights we could test in our data. An additional theoretical insight from allowing skills to depreciate is that the larger the rate of depreciation, the less the effect of a technological shock. Taken to its extreme, if skills depreciate completely each period then the technological shock has no effect on players.

is determined exogenously. This modeling assumption focuses attention on the player's choice of direction of investment, rather than the level of investment. These assumptions give us the following laws of motion for skills:

$$\Delta \log x_{ia} = \log x_{ia} - \log x_{i,a-1} = \frac{\lambda_r}{\lambda_r^2 + (1 - \lambda_r)^2} \left( \alpha_a + \epsilon_{ia} \right) \tag{1}$$

$$\Delta \log y_{ia} = \log y_{ia} - \log y_{i,a-1} = \frac{1 - \lambda_r}{\lambda_r^2 + (1 - \lambda_r)^2} \left(\alpha_a + \epsilon_{ia}\right) \tag{2}$$

These skill-specific laws of motion imply that, in the absence of any changes in racquet technology, the player's overall quality evolves according to

$$\Delta \log q_{iar} = \log q_{iar} - \log q_{i,a-1,r} = \lambda_r \Delta \log x_{ia} + (1 - \lambda_r) \Delta \log y_{ia}$$
$$= \alpha_a + \epsilon_{ia}$$
(3)

We assume  $\alpha_1 > \alpha_2 > \alpha_3 > 0$  so that a player's quality, in expectation, grows over his career and is concave. Heterogeneity in player quality arises over time because of the shocks  $\epsilon_{ia}$ , since those who receive favorable shocks end up with higher quality than those who do not.

## 3.3 Player quality and earnings

At the beginning of each period, a player must choose whether to play tennis *before* observing his shock. If a player plays tennis in period t, he earns  $q_{ia_i(t)r} \cdot p(Q_t)$ , where  $Q_t = \sum_j q_{ja_j(t)r}$ , p(Q) is continuous and differentiable, and p'(Q) < 0.8 If he chooses not to play, then he earns a wage  $w_0$ .

<sup>&</sup>lt;sup>8</sup>The summation in the expression for  $Q_t$  is over all players who are playing tennis in period t.

#### 3.4 Entry and exit

Each period unfolds in the following order:

- 1. A period begins.
- 2. Players decide whether to play or not. If a player does not play, he receives a wage  $w_0$ . Once he decides not to play, he may not rejoin the tour later.
- 3. Players decide which racquet technology to use.
- 4. Players choose their direction of investment. The optimal investment depends on  $\lambda_r$ , the relative weight the racquet places on one skill over another.
- 5. Players receive their quality shocks  $\epsilon_{ia}$  and their new qualities are realized  $\log q_{iar} = \log q_{i,a-1,r} + \alpha_a + \epsilon_{ia}$ .
- 6. The player, if he plays tennis, receives his wage  $q_{iar} \cdot p(Q_t)$ .

Players choose whether to play, which technology to use, and the direction of their investment to maximize their expected earnings. Recall that players only live for three periods.<sup>9</sup>

The present value of a player's earnings when he is age a at the start of period t is

$$V_a^t \left(q_{a-1}, \vec{z}_{t-1}\right) = \max \left\{ \underbrace{\mathbb{E}\left[q_a \cdot p(Q_t) + \beta V_{a+1}^{t+1}(q_a, \vec{z}_t) \mid q_{a-1}, \vec{z}_{t-1}\right]}_{\text{expected value of playing for one more year}}, \underbrace{\sum_{\tau=a}^{3} \beta^{\tau-a} w_0}_{\text{outside option}} \right\},$$

<sup>&</sup>lt;sup>9</sup>Allowing for an arbitrary number of periods does not change our results.

for  $a \in \{1,2,3\}$ . In the final year of a player's career the continuation value is zero:

$$V_4^{t+1}(q_3, \vec{z}_t) = 0.$$

The vector of aggregate state variables is  $\vec{z}_{t-1} = (m_{1,t-1}, m_{2,t-1}, \widehat{q}_{2,t-1})$ .  $m_{1t}$  and  $m_{2t}$  denote the masses of young and middle-aged players who choose to play in period t.  $\widehat{q}_{2t}$  denotes the threshold quality for participation of middle-aged players, so that a middle-aged player in period t plays if, and only if,  $q_{i1}$  is above  $\widehat{q}_{2t}$ . Last period's quality threshold for middle-aged players appears as a state variable because it affects the quality of old players in period t. A similar threshold exists for old players, but it does not enter as a state variable because the players who were old last period are no longer playing tennis. An individual player's quality appears as a state variable for middle-age and old players. It does not appear for young players because young players all start the period with the same quality  $q_0$ .

The participation thresholds  $\hat{q}_{2t}$  and  $\hat{q}_{3t}$  are defined by the requirement that a player at the threshold is indifferent between playing or not:

$$[\widehat{q}_{2t}]: \quad \mathbb{E}\left[q_2 \cdot p(Q_t) + \beta V_3^{t+1}(q_2, \vec{z}_t) \mid q_1 = \widehat{q}_{2t}, \vec{z}_{t-1}\right] = (1+\beta)w_0,$$

$$[\widehat{q}_{3t}]: \quad \mathbb{E}\left[q_3 \cdot p(Q_t) \mid q_2 = \widehat{q}_{3t}, \vec{z}_{t-1}\right] = w_0.$$

Since young players are identical when they decide whether to play or not, the mass of players who enters,  $m_{1t}$ , is determined by the requirement that all young players are indifferent between playing or not:

$$[m_{1t}]: \mathbb{E}\left[q_1 \cdot p(Q_t) + \beta V_2^{t+1}(q_1, \vec{z}_t) \mid \vec{z}_{t-1}\right] = (1 + \beta + \beta^2)w_0.$$

We assume that there is always an interior solution for  $m_{1t}$ .

The masses of middle-aged and old players that choose to play tennis in period *t*, are given by

$$m_{2t}=m_{1,t-1}\cdot \mathbb{P}\left[q_1\geq \widehat{q}_{2t}
ight]$$
, and 
$$m_{3t}=m_{1,t-2}\cdot \mathbb{P}\left[q_1\geq \widehat{q}_{2,t-1}\wedge q_2\geq \widehat{q}_{3t}
ight].$$

Putting these expressions together, the total quality of all players,  $Q_t$ , is given by

$$Q_{t} = m_{1t} \mathbb{E} [q_{1}] + m_{2t} \mathbb{E} [q_{2} \mid q_{1} \geq \widehat{q}_{2t}] + m_{3t} \mathbb{E} [q_{3} \mid q_{1} \geq \widehat{q}_{2,t-1} \land q_{2} \geq \widehat{q}_{3t}].$$

#### 3.5 Three useful lemmas

We now present three lemmas that will be useful later. All three are fairly intuitive, and their proofs (and all other proofs) have been relegated to the appendix.

**Lemma 1.**  $V_a^t$  is increasing in player quality for all  $a \in \{1,2,3\}$ . That is,

$$q' > q \Rightarrow V_a^t \left( q', \vec{z}_{t-1} \right) \ge V_a^t \left( q, \vec{z}_{t-1} \right).$$

Moreover, these inequalities are strict if the player chooses to play in period t rather than take the outside option.

**Lemma 2.** There exists a unique value for  $\hat{q}_{2t}$  (and  $\hat{q}_{3t}$ ) such that middle-aged (old) players in period t choose to play when  $q > \hat{q}_{2t}$  ( $q > \hat{q}_{3t}$ ), while those with quality  $q < \hat{q}_{2t}$  ( $q < \hat{q}_{3t}$ ) choose to exit and take the outside option.

**Lemma 3.** Suppose the market is in a steady state. Then  $\hat{q}_{3t} \geq \hat{q}_{2t} \geq \hat{q}_{1t}$ . That is, as players age their exit cutoffs also (weakly) rise.

The intuition for Lemma 3 is that younger players are willing to play with a lower quality in the current period, even if expected earnings are below  $w_0$ , because they anticipate enjoying a higher quality, and thus higher earnings, in the future. In contrast, old players have no future period so they will only be willing to play if their expected earnings are above  $w_0$ .

## 4 Effect of introducing a new racquet technology

We use our model to understand how players are affected by the introduction of composite racquets. For notational simplicity, we drop the r subscript and denote variables relating to the new racquet (i.e., the composite racquet) with a prime (i.e.  $\lambda'$  vs  $\lambda$ ). Without loss of generality, we assume  $\lambda > .5$ . We model the introduction of composite racquets as a new technology with A' > A, so that the racquet is better overall, and  $\lambda' < \lambda$ , so that it shifts weight away from x: the previously technologically-favored skill. We assume A' is sufficiently larger than A such that all players switch in the same period. The model offers us three predictions to take to the data.

 $<sup>^{10}</sup>$ As discussed in Section 2, the actual shift took place over a few years. Relaxing the assumption that A' is sufficiently larger than A so that all players switch does not change the results, as it simply truncates the distribution of changes in player quality (the soon to be defined  $u_{it}$ ) at zero. Thus the magnitude of changes would be different, but which players are helped and hurt, and the consequences of this, is not.

When a player switches to the new racquet his quality grows according to

$$\Delta \log q'_{ia} = \log q'_{ia} - \log q_{i,a-1}$$

$$= \log A' - \log A + \lambda' \log x_{ia} - \lambda \log x_{i,a-1}$$

$$+ (1 - \lambda') \log y_{ia} - (1 - \lambda) \log y_{i,a-1}$$

$$= \alpha_a + \epsilon_{ia} + \log A' - \log A + (\lambda' - \lambda) (\log x_{i,a-1} - \log y_{i,a-1})$$
 (4)

where  $q'_{ia}$  is player i's quality using the new racquet. Defining

$$u_{ia} = \log A' - \log A + (\lambda' - \lambda) \left( \log x_{i,a-1} - \log y_{i,a-1} \right), \tag{5}$$

#### (4) becomes

$$\Delta \log q'_{ia} = \alpha_a + \epsilon_{ia} + u_{ia} = \Delta \log q_{ia} + u_{ia} \tag{6}$$

Thus the introduction of a new racquet technology induces a one-time change,  $u_{ia}$ , in the growth of a player's quality. The magnitude of the change in player quality depends on the nature of the technological shock, with the magnitude increasing in both A' - A and  $|\lambda' - \lambda|$ . Furthermore, this change varies across players and depends on a player's mix of skills x and y. A player with relatively more of the skill the new racquet puts additional weight on, so  $\log x_{i,a-1} - \log y_{i,a-1}$  is relatively small, experiences a larger  $u_{ia}$  and sees his quality relative to other players increase. Likewise, a player with relatively less of this skill experiences a smaller  $u_{ia}$  and sees his relative quality fall.<sup>11</sup>

Because players targeted their prior investments to the mix of skills that was optimal for the old racquet, the new racquet helps lower quality players, who

<sup>&</sup>lt;sup>11</sup>In order for players to want to switch, it must be that switching improves their quality, so  $u_{ia} \ge 0$ . This will be the case if, for instance, A' is sufficiently larger than A.

have not invested as much (either due to being younger or to receiving smaller  $\epsilon_{it}$  shocks), more than it helps better players, who have. The following proposition shows this formally.

**Proposition 1** (Shock hurts better players). *If player i was better than player j in the* prior period (i.e.,  $q_{i,a_i(t-1)} > q_{j,a_j(t-1)}$ ) then a technological shock that shifts weight away from the favored skill reduces the quality of player i relative to the quality of player j (i.e.,  $u_{ia_i(t)} < u_{ja_i(t)}$ ).

Furthermore, the technological shock, on average, benefits younger players at the expense of older players. It helps younger players because they have not spent their periods of skill acquisition acquiring the "wrong" mix of skills. Figure 3 illustrates the evolution of player quality over time and how the effect of the new racquet varies by the age of the player. As the figure illustrates, player quality is climbing over time, but when the new racquet arrives it helps those who begin their careers immediately after its arrival much more than it helps older players. This will give younger players a relative advantage over their more experienced peers and they will generally perform better than expected for their age. We formally show this in the following proposition.

**Proposition 2** (Shock hurts older players on average). Suppose player i is older than player j when the new technology arrives. Also suppose that we were in a steady state before the new technology. Then a technological shock in period t that shifts weight away from the favored skill more likely than not reduces the quality of player i relative to the quality of player j. That is,  $\mathbb{P}\left[u_{ia_i(t)} < u_{ja_j(t)}\right] > .5$ .

Because older players have been hurt relative to younger players, it seems reasonable to conjecture that older players would start retiring sooner while younger

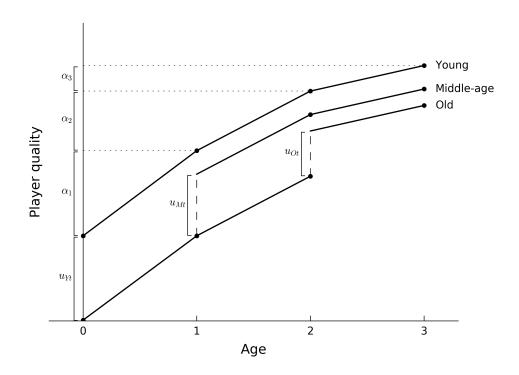


Figure 3: Change in quality trajectory when composite racquet technology arrives

*Notes:* "Young" players are in their first period when the new racquet arrives. "Middle-aged" and "old" players are in periods two and three of their careers when the new racquet arrives. The quality trajectories are displayed with all shocks set to zero.

players will exit less often. However, the new technology has an ambiguous effect on exit rates. To see why the effect on exit rates is ambiguous, consider an old player who is right at the exit threshold at the time of the technological shock. If the demand curve for his output is perfectly elastic (p'(Q) = 0) so that the price he receives per unit of quality is unchanged by the new technology, then his earnings are higher,<sup>12</sup> and he now strictly prefers to continue playing tennis. Thus, the exit rate for old players will decrease. Now consider another extreme case where demand is not perfectly elastic, but  $\lambda = 1$  and  $\lambda' = 0$ . The technological shock completely devalues all investments the older player has made and his quality is now equal to that of the youngest players. Hence, his expected earnings that period are the same as that of a new player. However, a new player is willing to earn less than  $w_0$  in the first period because he expects his quality, and thus earnings, to grow in the future. Thus, the old player expects to earn less than  $w_0$  and strictly prefers to exit instead.

Our simple model provides one more prediction about the period-to-period rank correlation of player quality. Because the technological shock hurts older and better players, it also leads to a "reshuffling" of which players are good and which are not. The next proposition shows that the technological shock reduces the probability that a player who was better than another in the last period continues to be better, thereby reducing the period-to-period rank correlation of player quality.

**Proposition 3** (Rank correlation falls). A technological shock that shifts weight away from the favored skill temporarily reduces the rank correlation, as measured by Kendall's  $\tau$ , in player quality over time.

In summary, this simple model guides us in measuring the effect of the intro-

<sup>&</sup>lt;sup>12</sup>His earnings are higher since his own quality has risen.

duction of composite racquets on three outcomes in the data. First, the model predicts the new racquets will help younger players relative to older players. Second, although it seems intuitive that the arrival of composite racquets would cause older players to retire at higher rates, the theoretical effect turns out to be ambiguous, leaving the effect of composite racquets on exit as an empirical question. Finally, the model predicts the new racquets will temporarily reduce the rank correlation in player quality over time. We test these predictions using data on the universe of men's professional tennis matches.

#### 5 Data

To test our theoretical predictions of the effect of a skill-altering technological change on players, we use data on all men's professional tennis matches played between 1968 and 2014.<sup>13</sup> The data were generously provided by the ATP World Tour, the governing body for men's professional tennis. For each match, we observe the winner and loser of the match and the score. The data also contains background information about players such as date of birth. The data does contain information about tournament prize money, but this data is very incomplete prior to 1990. We use data from all main draw matches at Grand Slams, regular Tour events, Davis Cup, and the Challenger tour.<sup>14</sup> All of these events award ATP ranking points, which determine a player's official ranking, and therefore his

<sup>&</sup>lt;sup>13</sup>Women's professional tennis is governed by the Women's Tennis Association (WTA) which is entirely independent of the ATP. Although the ATP and WTA are comparable in size and popularity today, during the 1970s the WTA was significantly smaller than the ATP. Therefore, in this paper we focus on men's professional tennis.

<sup>&</sup>lt;sup>14</sup>We exclude qualifying rounds because we do not have data on them prior to 2007. We also exclude matches from the International Tennis Federation's Satellite and Futures tournaments because of incomplete data; these events are the lowest level of events which award ATP ranking points (i.e., they award the fewest number of ranking points and the least amount of prize money).

eligibility for, and seeding in, future tournaments. 15

We only include players who appear in the strongly connected component (SCC), essentially limiting ourselves to those who both won and lost at least one match in a calendar year. 16 Although the SCC could be quite small in principle, in practice it contains the majority of players in the data and the vast majority of matches. <sup>17</sup> Defining active players as those in the strongly connected component has the practical effect of eliminating players who compete in a very small number of matches, on average just 1.6 matches. These are typically young players who are actively competing in lower level (non-Tour) events in the hope of becoming a regular competitor on the Tour, but who have not yet been able to make more than one or two Tour appearances. Limiting ourselves to the strongly connected component reduces the number of player-years in our sample by 44 percent but only reduces the number of matches by 9 percent. Figures 4a and 4b show how the number of matches and players in the SCC evolves over time, Figure 4c shows how the number of tournaments has grown with time. Figure 4d shows that, other than for 1968 and 1969, the fraction of data in the SCC is consistent over time. In light of the limited data for 1968 and 1969, we omit these years from our analysis. 18

Professional tennis players are typically between the ages of 18 and 35. Most professionals begin their careers around ages 18 to 20, and few careers last more than 15 years (see Figure 5). From Table 1, we see that the average career consists

<sup>&</sup>lt;sup>15</sup>"What is the Emirates ATP Rankings?" ATP World Tour, accessed 26 September 2016, http://www.atpworldtour.com/en/rankings/rankings-faq.

<sup>&</sup>lt;sup>16</sup>More precisely, think of all the players in the data as points in a directed graph. Player i is connected to player j by a (directed) edge if i defeated j (and vice versa). The SCC is the maximal subgraph of this directed graph such that, for any two players i and j in the SCC, there exists a directed path from i to j and from j to i.

<sup>&</sup>lt;sup>17</sup>A match appears in the SCC only if both of its players are in the SCC.

<sup>&</sup>lt;sup>18</sup>Professional and amateur tennis officially merged in 1968, known today as the beginning of the "Open Era." However, the transition took a couple of years and wasn't complete until 1970 or so. This is likely to be the reason why data are more limited prior to 1970.

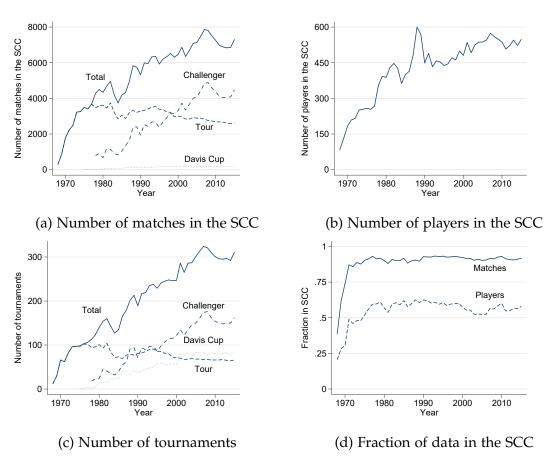


Figure 4: Trends in tour size over time

Table 1: Career summary statistics

	Mean	Median	Std. dev.
Age of entry	20.7	20.4	2.69
Number of years active	6.12	5	4.53
Career singles wins	87.1	29	130.6
Career singles matches	167.0	69	218.0
Observations	2541		

*Notes:* These summary statistics are only calculated for years in which a player appeared in the strongly connected component, but include all of their wins and matches in those years, regardless of whether their opponent was in the strongly connected component. The table is limited to players born between 1950–1985, so that we have had a chance to observe (almost) all of their career.

of about six active years of play.

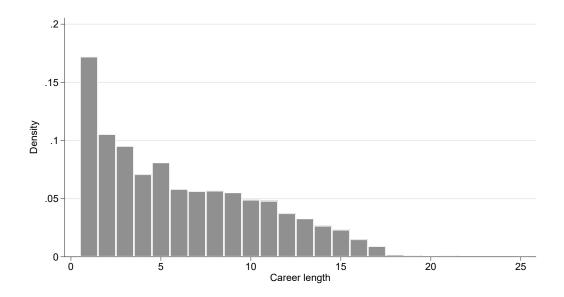


Figure 5: Histogram of number of years active on the tour

As Table 2 shows, the typical player only plays 26 matches per year although this variable has a large right tail. The tail arises because, unlike many other sports where teams play a fixed number of games in a season, tennis players compete in a tournament format. The tournament format causes more successful players to play many more matches than others over the course of a year. To illustrate,

Table 2: Player-year summary statistics

	Mean	Median	Std. dev.
Age	24.3	23.8	4.09
Annual singles wins	13.6	9	13.9
Annual singles matches	26.1	21	21.1
Observations	20275		

*Notes:* These summary statistics are only calculated for those in the strongly connected component, but include all of their wins and matches, regardless of whether their opponent was in the strongly connected component.

consider a tournament with 64 players. Half of these players will lose in the first round and therefore will play only one match. At the other extreme, the winner and runner-up of the tournament will each play 6 matches. As the best players are invited to more tournaments, this effect compounds over the course of the year so that the best players end up playing many more matches than the typical player.

The tournament format also complicates the interpretation of statistics like a player's win rate. In sports with a fixed number of games in a season, a team's win rate provides a reasonable measure of success. In this case, win rates average 50 percent by construction, making them a useful benchmark for distinguishing winning and losing records. In tennis, the win rate is much more difficult to interpret. Returning to the example of a 64 player tournament, half of the players have a win rate of zero, one-quarter have a win rate of 50 percent, and so on. The average win rate among all 64 players is actually 30.7 percent. Thus, in any tournament the average tennis player has a "losing record," and only the top quarter of players will have win rates in excess of 50 percent.

# 6 Estimating player quality

For estimation, we model player i's performance in match m as

$$\log \hat{q}_{im} = \log q_{it} + \mu_{im}$$

where  $q_{it}$  is i's quality in year t and  $\mu_{im}$  is a type 1 extreme value match-specific shock. Since a given match takes place during a specific year, we let the match subscript absorb the time subscript. Player i wins a match against player j if, and only if, he performs better in the match:  $\hat{q}_{im} > \hat{q}_{jm}$ .

Thus the probability that player i defeats player j in a match played in year t is given by the familiar logit expression

$$\mathbb{P}(i \text{ defeats } j) = p_{ijt} = \frac{q_{it}}{q_{it} + q_{it}}.$$
 (7)

and the likelihood of observing our data given these probabilities is

$$L = \prod_{i=1}^{N} \prod_{j=i+1}^{N} p_{ijt}^{w_{ijt}} (1 - p_{ijt})^{w_{jit}}$$

where  $w_{ijt}$  is the number of times i is observed defeating j in year t. We use data on match outcomes to estimate each player's quality in each year,  $q_{it}$ , by choosing  $q_{it}$  to maximize this likelihood.

We use the conditional logit model to estimate player quality because it incorporates information about the quality of a player's opponents. Players do not face a random sample of opponents, both because better players participate in more competitive tournaments, and because the further a player advances in any given tournament the better his competitors become. Simply calculating the fraction of matches won does not take into account that players with more matches have tended to play those matches against better opponents. For example, consider two players and two tournaments. Player A wins his first two matches at the first tournament but loses in the third round. He then loses in the first round of the second tournament, giving him a win rate of one-half. Player B makes it to the second round of the first tournament but is not invited to the second tournament, giving him the same win rate of one-half. Although A and B both won half of their matches, A's wins came against better opponents than did B's, and the conditional logit model takes this into account when estimating their qualities. However, none of our theoretical predictions rely on the conditional logit assumption. Rather, we make this assumption to allow us to estimate player qualities from the data.

A player's quality is only identified if he is in the strongly connected component, which means he must have both won and lost to another player in the strongly connected component. This is necessary because if a player never won a match, then to maximize the likelihood we need to set his probability of winning to zero by setting his quality to 0; and likewise if a player never lost a match then we need to set his probability of winning to one by setting his quality to  $\infty$ . A logit model cannot assign a finite (log) quality to these players, so we remove them. We iterate this process until no more players are removed. We define the remaining players as *active* and these are the players we use in our estimation.<sup>19</sup>

Our estimates of player quality within each year are only relative to other players within that year, because the probability that one player defeats another is unchanged if we add a constant to both players' qualities. Thus, we normalize the

<sup>&</sup>lt;sup>19</sup>This approach is essentially the same as that taken by Sorkin (2018).

estimates of (log) quality in a year to have a mean of zero, so the estimates must always be interpreted relative to the "average" player that year. This implies that, by construction, any trend in average quality has been removed.

# 7 Results

#### 7.1 Younger players gained relative to older players

Our model's first prediction is that the transition from wood to composite racquets should help younger players relative to older players. We test this in four ways.

First, as Figure 6 shows, the average age of the top sixteen players at Grand Slam events fell upon the introduction of composite racquets.<sup>20</sup> The dashed lines mark the years between the introduction of composite racquets (1978) and the first year all four Grand Slams were won using a composite racquet (1984).<sup>21</sup> The composite racquets allowed younger players to compete more successfully at the highest levels of play.

Second, younger players' ability to compete more successfully also increased the share of matches they played across the tour, and this increase came at the expense of older players. As Figure 7 shows, the players between ages 18 and 21 double their share of matches from 10 percent in the mid-1970s to 20 percent in the mid-1980s. This increase came at the expense of older players, ages 26 to 39, with the most severe drops appearing among players over 30 years old.

<sup>&</sup>lt;sup>20</sup>In men's tennis, the four Grand Slam events are the Australian Open, Roland Garros, Wimbledon, and the U.S. Open.

<sup>&</sup>lt;sup>21</sup>As Figure 2 shows, since 1984 only one Grand Slam has been won using a non-composite racquet.

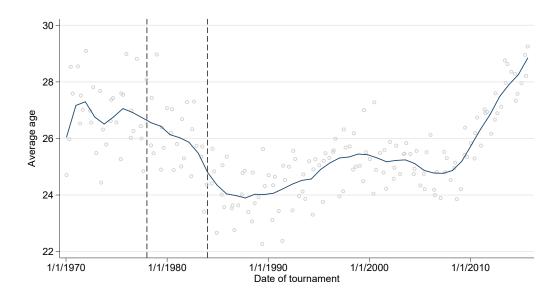


Figure 6: Average age in round of 16 of each Grand Slam over time

*Notes:* The figure plots the average age in the round of 16 for each Grand Slam (circles), and the results of smoothing the data with a local-linear regression (solid line). The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

But starting in the 1990s, younger players accounted for a diminishing share of matches, returning to 10 percent by 2015, while the share of older players recovered, ultimately returning to its previous level.

The U-shaped (and inverted U-shaped) pattern, where outcomes return to near their previous levels is important because it suggests that the effect of the new composite racquets was temporary. In particular, it does not seem to be the case that the composite racquets, by increasing the pace and intensity of play, made it impossible for older players to compete. Rather, the transition from wood to composite racquets temporarily disadvantaged older players because the skills they had spent their career investing in were no longer as valuable.

The U-shaped (and inverted U-shaped) pattern we see in Figures 6 and 7, and will see again in later figures, also is informative about how long it took for

professional tennis to respond to the introduction of the new composite racquets. Depending on the figure, it took until 2005–2010 for outcomes to return to the levels they were at before the composite racquet was introduced. Thus the transition in response to the new composite racquets lasted for roughly 30 years. If the average player has a career of about six years, then a 30-year transition corresponds to four generations of average professional tennis players. Because more successful players have longer careers (around 15 years), the transition lasted for two generations of more successful players. These estimates are similar in magnitude to those from Clark (2005), who estimates it took roughly 60 years for the technical innovations of the Industrial Revolution to lead to rising real wages.

We also use our estimates of player quality to more directly show younger players gained relative to older players. In Figure 8, we plot the median ages of players with above- and below-average (log) quality (i.e.,  $\log \hat{q}_{it} > 0$  and  $\log \hat{q}_{it} \leq 0$  respectively). In the early 1970s, above-average players tended to be older than below-average players. During the racquet transition the median age fell for both groups, but it declined far more quickly for above-average players, so that for a few years in the mid-1980s the median above-average player was no longer older than the median below-average player. Over the next two decades, the median age rose for both groups, again rising more quickly for above-average players. These swings in the median age are even more dramatic when considering that the typical professional tennis player actively participates in the tour for just 6 years.

Finally, Figure 9 plots the evolution of the correlation between players' ages and their estimated (log) quality over time. As Lemma 3 suggests, we find that older players are typically better than younger players. This occurs both because older players have more experience, and because older players retire when they are no

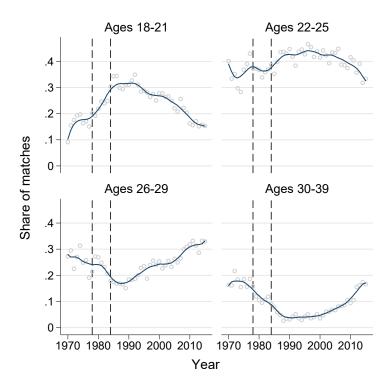


Figure 7: Share of matches by age group over time

*Notes:* The figure plots the share of matches by age group for each year (circles), and the results of smoothing the data with a local-linear regression (solid line). The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

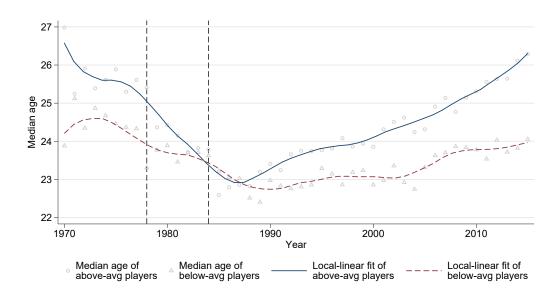


Figure 8: Median age of above- and below-average players over time

*Notes:* The figure plots the median age of above- and below- average players in each year (circles and triangles), and the results of smoothing the data with a local-linear regression (lines). Above-average players are those with an estimated (log) quality above zero. The vertical dashed lines mark the years when professional tennis players were transitioning to composite racquets.

longer being successful, while a younger player at the same level of success may keep trying to improve.<sup>22</sup> However, during the transition to composite racquets the correlation fell, and the point estimates even turn negative for a few years, before eventually recovering to their previous levels. For this period, unlike before and after, being older is not predictive of being better.

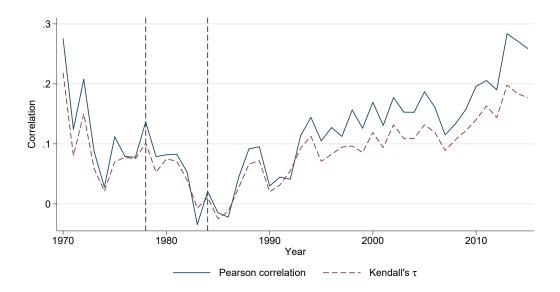


Figure 9: Correlation between estimated quality and age over time

*Notes:* The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

To put the changes in the correlation between quality and age into a monetary metric, we estimate the relationship between a player's estimated (log) quality and his (log) annual prize money. Unfortunately, we do not have any data about prize money prior to 1990, so we cannot look at the effects of composite racquets on prize money directly. However, we can regress a player's (log) annual prize money on his (log) estimated quality using data pooled from the first five years

<sup>&</sup>lt;sup>22</sup>In the model, younger players have lower exit thresholds than older players.

available—1990 through 1994 (see Figure 10).<sup>23</sup> We find that a one percent increase in a player's estimated quality corresponds to a 1.14 percent increase in prize money. Presuming this relationship between prize money and estimated quality has not changed over time, we can back out the implied OLS relationship between (log) earnings and age by

$$\beta_{prize,age} = \beta_{prize,qual} \times \beta_{qual,age} = 1.14 \times \beta_{qual,age}$$

where  $\beta_{y,x}$  denotes the OLS coefficient from regressing y on x. Figure 11 plots the implied OLS coefficient over time. Both before and after the racquet transition, being one year older was correlated with about five percent higher annual earnings. However, during the racquet transition this age gradient temporarily disappeared.

## 7.2 Exit rates of older players rose relative to younger players

Our model does not make a clear prediction about how the exit decisions of older players will respond to the technology shock. However, as shown in Figure 12, we find that exit rates rose during the racquet transition, most dramatically among older players. We define an "exit" to occur whenever a player is active in year t but is not active in year t + 1.24 During the racquet transition, players aged 22–25 and 26–29 saw their exit rates rise approximately ten percentage points from 10 to 20 percent and from 20 to 30 percent, respectively. Although it began prior to the racquet transition, the exit rate for players aged 30–39 saw an even more dramatic

<sup>&</sup>lt;sup>23</sup>We exclude any player-year observation with five or fewer matches and run a weighted regression, weighting each observation by the number of matches played. The rationale for weighting by number of matches is that players with more matches will have more precisely estimated values for quality, thereby helping to mitigate attenuation bias.

<sup>&</sup>lt;sup>24</sup>Although we rule it out in our model, this definition of "exit" implies that a player could exit (and re-enter) multiple times over his career. 29 percent of players do so.

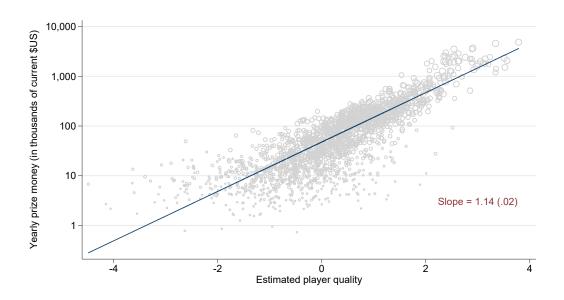


Figure 10: Estimated player quality and yearly prize money

*Notes:* The figure only includes data from 1990-1994 and players who played more than five matches in the year. Regression line and marker size weighted by number of matches played.

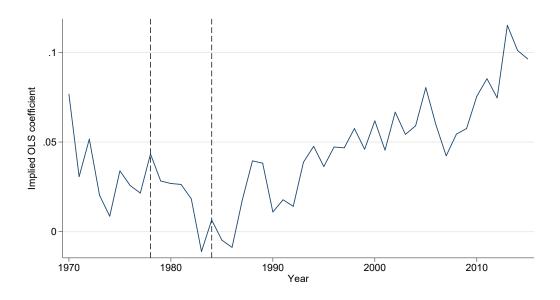


Figure 11: Implied age-earnings gradient

*Notes:* The implied OLS coefficient was calculated by regressing (log) estimated quality on age in each year and regressing (log) annual prize money on (log) estimated quality for the years 1990–1994. We then multiply these two numbers together to obtain the implied OLS coefficient from regressing (log) annual prize money on age in each year.

rise. Starting in the 1990s, however, the exit rates of players over age 25 declined, nearly returning to their previous levels.

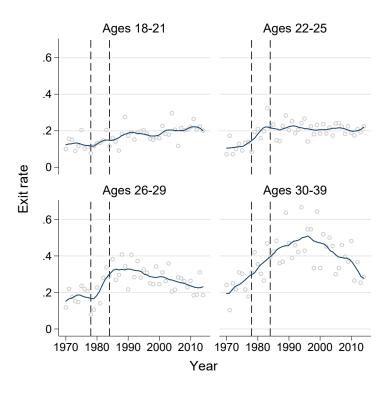


Figure 12: Exit rates by age group over time

*Notes:* The figure plots the exit rate by age group for each year (circles), and the results of smoothing the data with a local-linear regression (solid line). The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

During the transition from wood to composite racquets, young players found it easier to enter the tour and be successful. In Figure 13, we plot the average age at which a birth cohort first enters the tour against the age of that cohort in 1980, when the tour was transitioning from wood to composite racquets. We see that players who were around 10 years old in 1980 entered the tour at an average age of 20. But both older and younger cohorts entered as much as a year and a half later. Notably, players who were 10 years old in 1980 were among the first

players who had the opportunity to grow up playing with the composite racquets. Older cohorts, even those just a few years older, were forced to switch racquets mid-career. Recall that "entering the tour" here means that a player is in the strongly connected component. At a minimum, this means that a player must win and lose at least one match during the year. Thus, the age of entry we measure here indicates the first time a player had a substantial presence on the tour.

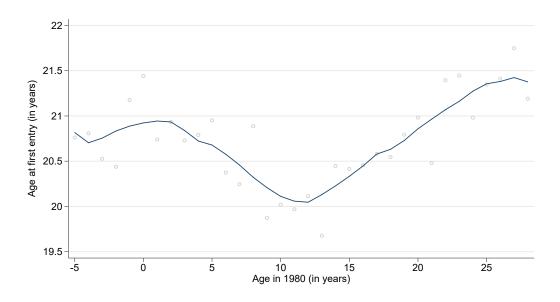


Figure 13: Age when first entered tour by age in 1980

*Notes:* The figure plots the mean age when first entered tour for each birth year, reported as age in 1980, (circles), and the results of smoothing the data with a local-linear regression (solid line).

The combination of increased exit rates for older players and earlier entry ages caused the age distribution of players on tour to compress and shift younger. Figure 14 plots the quartiles of the age distribution of all players on tour over time. During the late 1970s and early 1980s, the median age fell from 25 to 23 years old, and the 75th percentile fell even more dramatically from 29 to 25 years old. However, over time the distribution shifted back toward older ages, with the median age returning to 25 years old.

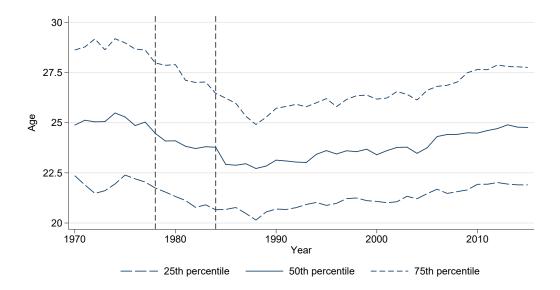


Figure 14: Age distribution over time

*Notes:* The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

# 7.3 Year-to-year rank correlation of player quality fell temporarily

The final prediction from our model is that the transition from wood to composite racquets should reduce the year-to-year rank correlation in player quality if older players tend to be better than younger players. As we saw in Figure 9, older players do tend to be better. Thus we expect the change in technology to lead to a "reshuffling" of players as some benefit more from the technology than others.<sup>25</sup>

Figure 15 verifies that this prediction holds up in the data. In each year, we calculate the rank correlation (Kendall's  $\tau$ ) between a player's estimated quality

<sup>&</sup>lt;sup>25</sup>It is possible for a change in technology to reinforce the status quo if it helps better players more than worse players. In our case, older players, who are more heavily invested in the skills needed to thrive with the old racquets, are better, and so we expect the new technology to lead to a reshuffling.

from one year to the next. As we would expect, this correlation is positive—players with better ranks in one year tend to have better ranks in the next year. This positive correlation has been rising over time, which may be due, in part, to increasing precision in our estimates due to players competing in more matches in later years. However, during the transition from wood to composite racquets, the rank correlation took a sudden dip before recovering to trend around 1990. This is consistent with a "reshuffling" hypothesis that some players benefited more from the new technology than others.

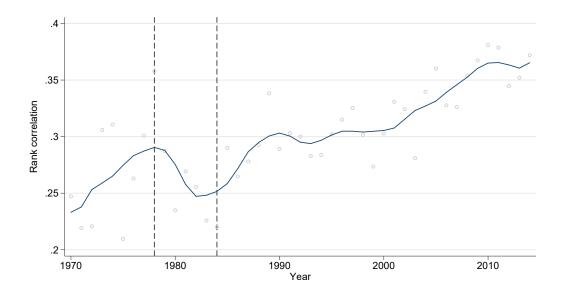


Figure 15: Year-to-year rank correlation of estimated player quality

*Notes:* This figure plots a measure of rank correlation (Kendall's  $\tau$ ) between a player's estimated quality in consecutive years (circles). If a player did not appear in year t but did in year t-1 or t+1, we imputed their quality to be below the minimum in year t. The solid line shows the data smoothed using a local-linear regression. The dashed lines mark the years when professional tennis players were transitioning to composite racquets.

## 8 Conclusion

We examine the effects of technological change within the context of a major innovation in men's professional tennis—the introduction of composite racquets in the late 1970s and early 1980s. We find that the introduction of the new composite racquets temporarily helped younger players at the expense of older players, reduced the rank correlation in player quality over time, and increased exit rates of older players relative to younger players. Over time, these temporary shifts largely reversed themselves, although the transition took two to four generations. These empirical findings are consistent with a model of skill-altering technological change.

Men's professional tennis provides an excellent setting for studying the effects of skill-altering technological change on workers for four reasons. First, we have detailed panel data on multiple cohorts of individual players, allowing us to track the long run impacts of the innovation. Second, the new technology arrived suddenly and rather unexpectedly and was also universally adopted within a few short years. Third, tennis careers are relatively short—six years on average and rarely more than 15 years—which allows us to follow multiple cohorts of players over their entire careers. Fourth, since we can observe the performance of a player without worrying about the effects of teammates, professional tennis offers us unusually clean measures of worker productivity.

While the magnitude of the effects we identify depend on the size of the technological shock (i.e., the change in  $\lambda$ ), and so will vary across settings,<sup>26</sup> these

<sup>&</sup>lt;sup>26</sup>For example, a technological innovation such as a nail gun for construction workers, or PVC and PEX pipes for plumbers, would map into our model as a relatively small change in  $\lambda$  and so have relatively small effects, whereas an innovation such as electronic typesetting for printers or autonomous vehicles for truck drivers map into our model as close to a zero-one change in  $\lambda$  and

effects will likely manifest themselves in other situations. As such this episode in men's tennis provides insights into current concerns regarding the effects of technological innovation on workers. When a new technology arrives—such as computer technology—current workers find it difficult to adopt the new technology because their skills are adapted for the prior technology. Thus, even though they may attempt to switch, they remain at a disadvantage to younger workers who have not spent valuable time learning to use the now-outdated technology. Older workers experience a relative decline in their productivity while younger workers receive a boost from being the first group of workers to take full advantage of the new technology. Although these effects are temporary, they can persist for several years, with permanent effects on middle-aged and older cohorts during the transition to the new technology.

Our findings highlight a previously unexplored channel through which technological change affects wages and employment patterns for workers. In periods with more skill-altering change, workers may face substantial risk in making investments in their skills because of the possibility that these investments may be rendered obsolete in the future. Moreover, this risk will be greater the more specialized the investment in skill. Thus, a better understanding of skill-altering technological change may contribute to our understanding of the dynamics of wages and the returns to human capital investment.

have very large effects.

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# A Online Appendix for Technological Change and Obsolete Skills: Evidence from Men's Professional Tennis

#### A.1 Proof of Lemma 1

*Proof.* We prove this by induction, and so begin with  $V_3^t$ . First, note that  $\mathbb{E}\left[q_3 \cdot p(Q_t) \mid q_2, \vec{z}_{t-1}\right]$  is strictly increasing in  $q_2$ , while the wage of the outside option  $w_0$  is unrelated to  $q_2$ . Thus,  $V_3^t$  is weakly increasing in  $q_2$  and strictly increasing if the player chooses to play in period t.

Now we turn to  $V_a^t$  and assume  $V_{a+1}^{t+1}$  is increasing in player quality. First, note that  $\mathbb{E}\left[q_a\cdot p(Q_t)+\beta V_{a+1}^{t+1}(q_a,\vec{z}_t)\mid q_{a-1},\vec{z}_{t-1}\right]$  is weakly increasing in  $q_{a-1}$ . This is true because  $\mathbb{E}\left[q_t\cdot p(Q_t)\mid q_{a-1},\vec{z}_{t-1}\right]$  is strictly increasing in  $q_{a-1}$  while  $\mathbb{E}\left[\beta V_{a+1}^{t+1}(q_a,\vec{z}_t)\mid q_{a-1},\vec{z}_{t-1}\right]$  is weakly increasing in  $q_{a-1}$ . As before, the present value of the outside option,  $\sum_{\tau=0}^{3-a}\beta^{\tau}w_0$ , is unrelated to  $q_{a-1}$ . Thus,  $V_a^t$  is weakly increasing in  $q_a$  and strictly increasing if the player chooses to play in period t.

#### A.2 Proof of Lemma 2

*Proof.* An old player (a = 3) entering period t with quality  $q_2$  will continue playing if, and only if, the value of playing is no less than the outside option:

$$\mathbb{E}\left[q_3 \cdot p(Q_t) \mid q_2, \vec{z}_{t-1}\right] \ge w_0. \tag{8}$$

Note that

$$\lim_{q_2\to 0} \mathbb{E}\left[q_3 \cdot p(Q_t) \mid q_2, \vec{z}_{t-1}\right] = 0$$

$$\lim_{q_2\to\infty}\mathbb{E}\left[q_3\cdot p(Q_t)\mid q_2,\vec{z}_{t-1}\right]=\infty.$$

Also, note that the left-hand side of (8) is a strictly increasing, continuous function of  $q_2$ . Thus, as long as  $w_0$  is positive and finite, equation (8) will hold with equality at exactly one point. Therefore,  $\hat{q}_{3t}$  exists and is unique.

A middle-aged player entering period t with quality  $q_1$  will continue playing if, and only if, the value of playing for one more period is no less than the present value of the outside option:

$$\mathbb{E}\left[q_2 \cdot p(Q_t) + \beta V_3^{t+1}(q_2, \vec{z}_t) \mid q_1, \vec{z}_{t-1}\right] \ge (1+\beta)w_0. \tag{9}$$

The first term of the left-hand side of (9) is strictly increasing in  $q_1$ , while from Lemma 1 we know that the second term is weakly increasing in  $q_1$ . Thus, the entire term is strictly increasing in  $q_1$ . It also likewise follows that it is continuous. Following the same reasoning as the previous paragraph, it must be that  $\hat{q}_{2t}$  exists and is unique.

#### A.3 Proof of Lemma 3

*Proof.* We first show  $\hat{q}_{3t} \geq \hat{q}_{2t}$ . Since we are in a steady state, we drop the dependence on t. By way of contradiction, suppose that  $\hat{q}_2 > \hat{q}_3$ . Consider a

quality level  $q^* \in (\widehat{q}_3, \widehat{q}_2)$ . Then it must be the case that

$$\mathbb{E}\left[q_2 \cdot p(Q) + \beta V_3(q_2, \vec{z}) \mid q_1 = q^*, \vec{z}\right] < (1 + \beta)w_0 \tag{10}$$

$$\mathbb{E}[q_3 \cdot p(Q) \mid q_2 = q^*, \vec{z}] > w_0 \tag{11}$$

From (10) we can write

$$(1+\beta)w_0 > \mathbb{E} [q_2 \cdot p(Q) \mid q_1 = q^*, \vec{z}] + \beta \mathbb{E} [V_3(q_2, \vec{z}) \mid q_1 = q^*, \vec{z}]$$
  
 
$$\geq \mathbb{E} [q_2 \cdot p(Q) \mid q_1 = q^*, \vec{z}] + \beta w_0$$

Combining this with (11) we get

$$\mathbb{E}[q_2 \cdot p(Q) \mid q_1 = q^*, \vec{z}] < w_0 < \mathbb{E}[q_3 \cdot p(Q) \mid q_2 = q^*, \vec{z}]$$

But this is a contradiction because the distribution of  $q_2 \mid q_1 = q^*$  first-order stochastically dominates the distribution of  $q_3 \mid q_2 = q^*$ , which means it must be the case that

$$\mathbb{E}[q_2 \cdot p(Q) \mid q_1 = q^*, \vec{z}] > \mathbb{E}[q_3 \cdot p(Q) \mid q_2 = q^*, \vec{z}].$$

which is a contradiction. It is straightforward to extend this proof to show  $\widehat{q}_{2t} \geq \widehat{q}_{1t}$ .

# A.4 Proof of Proposition 1

*Proof.* As players improve, they invest more in the skill that the racquet they are using puts more weight on. From (1) and (2) we know

$$\log x_{ia} - \log y_{ia} = \log x_{i,a-1} - \log y_{i,a-1} + \frac{2\lambda - 1}{\lambda^2 + (1 - \lambda)^2} (\alpha_a + \epsilon_{ia}).$$
 (12)

By iterating equation (12), we find

$$\log x_{ia} - \log y_{ia} = \log x_0 - \log y_0 + \frac{2\lambda - 1}{\lambda^2 + (1 - \lambda)^2} \sum_{\tau=1}^{a} (\alpha_{\tau} + \epsilon_{i\tau}).$$
 (13)

Similarly, iterating equation (3) gives

$$\log q_{ia} = \log q_0 + \sum_{\tau=1}^{a} (\alpha_{\tau} + \epsilon_{i\tau})$$

$$\Rightarrow \sum_{\tau=1}^{a} (\alpha_{\tau} + \epsilon_{i\tau}) = \log q_{ia} - \log q_0.$$
(14)

Substituting (14) into (13) yields

$$\log x_{ia} - \log y_{ia} = \log x_0 - \log y_0 + \frac{2\lambda - 1}{\lambda^2 + (1 - \lambda)^2} \left( \log q_{ia} - \log q_0 \right). \tag{15}$$

Substituting (15) into (5) gives us

$$u_{ia} = \log A' - \log A + (\lambda' - \lambda) (\log x_0 - \log y_0) + (\lambda' - \lambda) \frac{2\lambda - 1}{\lambda^2 + (1 - \lambda)^2} (\log q_{i,a-1} - \log q_0).$$
 (16)

This implies

$$u_{ia_{i}(t)} - u_{ja_{j}(t)} = (\lambda' - \lambda) \frac{2\lambda - 1}{\lambda^{2} + (1 - \lambda)^{2}} \left( \log q_{i,a_{i}(t-1)} - \log q_{j,a_{j}(t-1)} \right). \tag{17}$$

Since  $\lambda' < \lambda$  and  $\lambda > 0.5$ , (17) implies that  $u_{ia_i(t)} < u_{ja_j(t)}$ .

# A.5 Proof of Proposition 2

*Proof.* Given that we are in a steady state, we know from Lemma 3 that the distribution of quality for older players has a higher truncation point than the distribution for younger players. Moreover, the quality of older players is shifted right, relative to that of younger players, by  $\alpha_2$  and/or  $\alpha_3$ . For both reasons, the median quality of older players in period t is greater than the median quality of younger players in period t. This implies that  $\mathbb{P}\left[q_{ia_i(t)} > q_{ja_j(t)} \mid a_i(t) > a_j(t)\right] > .5$ . By Proposition 1, this implies  $\mathbb{P}\left[u_{ia_i(t)} < u_{ja_j(t)} \mid a_i(t) > a_j(t)\right] > .5$ .

# A.6 Proof of Proposition 3

Proof. First note that equation (3) implies

$$\log q_{ia_{i}(t)} - \log q_{ja_{j}(t)} = \log q_{i,a_{i}(t-1)} - \log q_{j,a_{j}(t-1)} + \alpha_{a_{i}(t)} - \alpha_{a_{j}(t)} + \epsilon_{ia_{i}(t)} - \epsilon_{ja_{j}(t)}$$
(18)

and equations (6) and (16) imply

$$\log q'_{ia_{i}(t)} - \log q'_{ja_{j}(t)} = \log q_{ia_{i}(t)} - \log q_{ja_{j}(t)} + u_{ia_{i}(t)} - u_{ja_{j}(t)}$$

$$= \underbrace{\frac{\lambda \lambda' + (1 - \lambda)(1 - \lambda')}{\lambda^{2} + (1 - \lambda)^{2}}}_{B} \left(\log q_{i,a_{i}(t-1)} - \log q_{j,a_{j}(t-1)}\right)$$

$$+ \alpha_{a_{i}(t)} - \alpha_{a_{j}(t)} + \epsilon_{ia_{i}(t)} - \epsilon_{ja_{j}(t)}. \tag{19}$$

Since  $\lambda > .5$  and  $\lambda' < \lambda$ , it must be the case that  $0 \le B < 1$ . Equation (18) implies

$$\mathbb{P}\left[\log q_{ia_{i}(t)} > \log q_{ja_{j}(t)}\right]$$

$$= \mathbb{P}\left[\epsilon_{ia_{i}(t)} - \epsilon_{ja_{j}(t)} > -\left(\log q_{i,a_{i}(t-1)} - \log q_{j,a_{j}(t-1)} + \alpha_{a_{i}(t)} - \alpha_{a_{j}(t)}\right)\right], \quad (20)$$

while equation (19) implies

$$\mathbb{P}\left[\log q'_{ia_{i}(t)} > \log q'_{ja_{j}(t)}\right] \\
= \mathbb{P}\left[\epsilon_{ia_{i}(t)} - \epsilon_{ja_{j}(t)} > -\left(B\left(\log q_{i,a_{i}(t-1)} - \log q_{j,a_{j}(t-1)}\right) + \alpha_{a_{i}(t)} - \alpha_{a_{j}(t)}\right)\right].$$
(21)

Equations (20), (21), and B < 1 together imply

$$\mathbb{P}\left(q'_{ia_{i}(t)} > q'_{ja_{j}(t)} \mid q_{i,a_{i}(t-1)} > q_{j,a_{j}(t-1)}\right) \\
< \mathbb{P}\left(q_{ia_{i}(t)} > q_{ja_{j}(t)} \mid q_{i,a_{i}(t-1)} > q_{j,a_{j}(t-1)}\right).$$
(22)

Since Kendall's  $\tau$  has the property that  $E(\tau) = \mathbb{P}(x_{it} > x_{jt} \mid x_{i,t-1} > x_{j,t-1}) - \mathbb{P}(x_{it} < x_{jt} \mid x_{i,t-1} > x_{j,t-1})$ , equation (22) implies that the introduction of the new racquet reduces the rank correlation of period-to-period player quality in the period when the racquet is introduced.

## A.7 Discussion of heterogeneous initial skills

In general, allowing for heterogeneous initial skills complicates the analysis without adding additional insight. However, an alternative model we could consider is one where players are born with heterogeneous skills, and, while players could improve both skills, they could not change their initial mix of skills. In this model a change in racquet technology would change the type of players who enter. This alternative model leads to an important additional interpretation of our results: that technological change can hurt some workers who are born without the skills needed to succeed.

This alternative model has many of the same predictions as our model, however it leads to a very different prediction regarding player entry and exit. The alternative model predicts that young players who entered before the racquet change will exit at higher rates when the new racquet is introduced. The intuition for this is that while older players see their quality fall, given their lifetime of investment, many of them can still profitably play while the new players, whose endowment of skill better match the racquet, develop their skills. On the other hand, many young players who entered before the racquet change were playing at a loss, relative to their outside option, to develop the skills to earn profits later in their careers. With the racquet change, they no longer have the endowment of skills needed to have a probable path towards earning profits, and so will exit.

Put differently, in the alternative model, the new racquet leads to a much larger decrease in the continuation value for existing players. This change in continuation values affects younger players more than older players. At its extreme, this would lead to nearly all players in the second year of their professional career exiting.

As Figure 12 shows, we find that exit rates for the young are basically unchanged, while exit rates for the old climb significantly. This suggests that the alternative model does not match the data from professional tennis.