1-1-2015

Essays in Asset Pricing and Applied Micro-Economics

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Abstract
In the first chapter, Christian Goulding and I present a model of asset prices with recursive preferences and the simple consumption growth dynamics of Mehra and Prescott (1985) but relax the assumption that preference parameters are constant over time. We show that rare, temporary, and plausible fluctuations in the elasticity of inter-temporal substitution (EIS) and risk aversion (RA) can quantitatively explain numerous regularities in U.S. asset prices including: the equity premium and risk-free rate puzzles, excess return and consumption growth predictability, a counter-cyclical risk premium and an upward-sloping real yield curve. A novel implication is that time-varying EIS is more important than time-varying RA for explaining many of these regularities, suggesting a new source of risk in investors' ability to plan their consumption over long horizons. In addition, our model can accommodate a behavioral interpretation of psychological factors (e.g. fear) that drive fluctuations in asset prices beyond traditional risk factors.

The second chapter is an empirical study of the value of star college athletes. Collegiate athletes in the U.S. are not allowed to be paid directly for their athletic ability. Under the current regulations imposed by the NCAA, any compensation beyond scholarships and grant-in-aid to cover some basic living expenses is forbidden. This artificial constraint on athletes' wages, when university athletic programs are generating significant revenues, has sparked much recent debate over the compensation of college athletes. To help inform this debate, I quantify the value of a NCAA Division 1 FBS (Football Bowl Subdivision) star football and NCAA Division 1 star basketball players by estimating their marginal revenue product using a novel dataset of individual player and team performance statistics and publicly available athletic program revenue data. I find that a star college football player is worth up to $1.2-$2.1 million while star college basketball players are worth up to $655,000-$1.1 million a year. Interestingly, I also find evidence suggesting that a college recruiter's ability to identify revenue generating star players is limited and that the marginal revenue product of star college players declines as the team's media coverage increases.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Applied Economics

First Advisor
Kent Smetters

Keywords
Consumption based asset pricing, Pay for play, Star college athletes, Time varying preferences

Subject Categories
Economics | Finance and Financial Management

ESSAYS IN ASSET PRICING AND APPLIED MICRO-ECONOMICS

Mark William Clements

A DISSERTATION

in

Applied Economics

For the Graduate Group in Managerial Science and Applied Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2015

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ESSAYS IN ASSET PRICING AND APPLIED MICRO-ECONOMICS

Dedicated to

My parents Bill and Teresa Clements, parents and human beings of the highest caliber and without equal. Your unconditional love and support over the years is a gift I will never be able to match or repay. Thank you.

ACKNOWLEDGEMENT

I would like to thank my family and friends who have supported me over these many years in my pursuit of my educational and goals. To my committee, Kent, Jeremy, and Vincent - thank you for taking the time out of your busy lives to advise me and encourage me along each step of this oftentimes daunting and protracted process. Kent, thank you for taking the extra time out of your schedule necessary to chair my committee. I appreciate your deep economic insight and your awareness of how my research pertains to both practical applications and research that others are actively engaged in. Vincent, thank you for your clear and incisive guidance, particularly in helping me frame my research in a way that cuts through the noise and clearly underlines the most important results and interpretations. Jeremy, thank you for always making time to meet with me, meeting with me often, and for asking questions that always push me toward thinking about things in new ways. I would also like to thank Sterling Horne, Henry Bergquist, and Ram Yamarthy for their extremely helpful discussions and perpetual willingness to act as sounding boards for me in my journey to complete this dissertation. To my friends Paul Weimer and Matthew Zollinger, thank you for always being there with equal parts distraction and encouragement, often provided precisely at the times I needed it the most.

ABSTRACT

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Mark William Clements

Kent Smetters

In the first chapter, Christian Goulding and I present a model of asset prices with recursive preferences and the simple consumption growth dynamics of Mehra and Prescott (1985) but relax the assumption that preference parameters are constant over time. We show that rare, temporary, and plausible fluctuations in the elasticity of inter-temporal substitution (EIS) and risk aversion (RA) can quantitatively explain numerous regularities in U.S. asset prices including: the equity premium and risk-free rate puzzles, excess return and consumption growth predictability, a counter-cyclical risk premium and an upward-sloping real yield curve. A novel implication is that time-varying EIS is more important than time-varying RA for explaining many of these regularities, suggesting a new source of risk in investors' *ability to plan* their consumption over long horizons. In addition, our model can accommodate a behavioral interpretation of psychological factors (e.g. fear) that drive fluctuations in asset prices beyond traditional risk factors.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER 1 : Preference Irregularities and Asset Pricing Regularities.

1.1 Introduction

Following Mehra and Prescott (1985), an enormous literature in consumption-based asset pricing models has attempted to explain the equity premium puzzle and other stylized facts of asset prices with varying degrees of success.[1] Many models propose more complicated consumption dynamics than those in Mehra and Prescott (1985) in an attempt to capture sources of excluded risk in the consumption channel. However, the observed time series for aggregate consumption growth in the U.S. data is very smooth (Campbell and Deaton (1989), Campbell and Mankiw (1989)). Given this modest volatility, it is no surprise that modeling the risk faced by investors as coming exclusively from consumption risk leads to difficulty generating many of the stylized facts of asset prices.[2] Other models (e.g. Constantinides (1990), Weil (1989) and Epstein and Zin (1989)) propose alternative preference specifications to the standard constant relative risk aversion (CRRA) preferences of Mehra and Prescott (1985) with limited success. A more recent literature that explores alternatives to standard CRRA preferences suggests that counter-cyclical risk aversion (RA) is an important feature for improving the standard model.[3] Moreover, recent empirical work by

[1]Leading models in this literature fall roughly into three schools of thought: habits, long-run risks and rare disasters. The habits framework of Campbell and Cochrane (1999) argues that shocks to the current level of consumption that move consumption relative to habit (a moving average of past consumption) explain aggregate asset prices. The long-run risks models of Bansal and Yaron (2004) and Bansal, Kiku, and Yaron (2012) argue that shocks to expected long-run consumption growth, an unobservable component in the consumption growth process, and time-varying consumption volatility are crucial for explaining fluctuations in asset prices. The rare disasters literature (Rietz (1988), Barro (2006), Gabaix (2012) and Wachter (2013), among others) points to large and rare drops (disasters) in consumption and changes in the severity or probability of these disasters as crucial for explaining asset prices.

[2]For example, Julliard and Ghosh (2012) provide arguments and evidence suggesting that the rare disasters framework is an unlikely explanation of the equity premium puzzle.

[3]Campbell and Cochrane (1999) generate time-varying risk aversion through the surplus ratio of an external habit relative to current consumption. Gordon and St-Amour (2000, 2004) accomplish this by modeling the time-varying risk aversion parameter directly in the CRRA utility function. Melino and Yang (2003) do something similar under recursive preferences. Barberis, Huang, and Santos (2001) generate time-varying risk aversion through time-varying loss aversion that enters directly into Prospect Theory's value function. Routledge and Zin (2010) achieve this time-variation through variation in the endogenously determined probability of disappointment with generalized disappointment aversion preferences that overweights lower-tail outcomes.

Guiso, Sapienza, and Zingales (2013) and Cohn, Engelmann, Fehr, and Marechal (2013) provides direct evidence for counter-cyclical (and hence time-varying) risk aversion from survey and experimental data. These studies indicate that the standard assumption of constant preference parameters is a source of model misspecification.

Much less has been done in the consumption-based asset pricing literature exploring the assumption of a constant elasticity of inter-temporal substitution (EIS) as a potential source of model misspecification. Crossley and Low (2011) provide empirical evidence from consumer demand data that rejects the assumption of a constant EIS. Guvenen (2009) shows that a two-agent model with limited stock market participation and *heterogeneity* in the EIS is consistent with prominent features of asset prices.[4] Melino and Yang (2003) present an asset pricing model with recursive preferences that allows for both time-varying risk aversion *and* EIS parameters that is able to match the first two moments of equity returns and risk-free rates. A more recent paper by Kamstra, Kramer, Levi, and Wang (2014) shows that seasonal variation in the EIS improves the ability of their representative agent asset pricing model to match the seasonal patterns of equity and Treasury returns.

To explore further the importance of time-varying EIS for asset prices, we present a consumption-based asset pricing model with recursive preferences, along the lines of Epstein and Zin (1989), that relaxes the standard assumption of constant preference parameters but maintains the consumption dynamics of Mehra and Prescott (1985). We model rare and temporary changes in the preference parameters that govern RA and the EIS as a joint Markov process with consumption growth, taking the shocks that drive temporary fluctuations in these parameters as exogenous.[5] Furthermore, changes in preference parameters are not permanent structural breaks. They are temporary, anticipated by investors with rational

[4] A related household finance literature allows for the EIS to be heterogeneous across households and vary with endogenous factors such as wealth (Attanasio and Browning (1995), Atkeson and Ogaki (1997, 1996), Álvarez Peláez and Díaz (2005), Guvenen (2006)).

[5] Possible interpretations of this modeling device are given in Section *1.2.9*

expectations, and are expected to revert to their regular values. Also, these changes are small to moderate in magnitude and plausible based on guidance from empirical studies (see Section 1.3). We show that allowing for time-varying preferences in this way is enough to simultaneously generate many stylized facts that have proven historically challenging for consumption-based asset pricing models to match. Furthermore, we show that time-varying EIS is a source of uncertainty that affects an investor's *ability to plan* their consumption profile over long horizons. This source of risk is distinct from the usual consumption risk that affects an investor's *ability to smooth* consumption and is important for the model to produce many of these challenging stylized facts.

In particular, under the baseline calibration of the model, the RA and EIS parameters are at their regular values the majority of the time. However, once about every 42 years RA is elevated to an irregular value while once about every 18 years the EIS parameter is depressed to an irregular value. Both parameters stay in states of irregular values for about 3 to 4 years on average. Our consumption process replicates that of Mehra and Prescott (1985) but is calibrated to annual data over the sample 1930-2013. With these dynamics for preference fluctuations and consumption growth our model is able to produce a high equity premium with a low risk-free rate, along with volatilities and first-order auto-correlations, that are consistent with the data. The model also generates the more challenging stylized facts on the predictability of price-dividends. For instance, the model yields double-digit excess return predictability by price-dividend ratios over long horizons. Furthermore, the model produces almost no predictability of consumption growth by price-dividends or predictability of price-dividends by lagged consumption growth. These are features that leading consumption-based asset pricing models are unable to generate simultaneously. The model also produces a volatile and counter-cyclical risk premium as well as a counter-cyclical Sharpe Ratio. Finally, the model is able to generate an upward sloping real yield curve with a ten-year yield of 1.62 and a 15 basis point spread over the short rate. This last feature is particularly difficult for consumption-based asset pricing models with

Epstein and Zin (1989) preferences to produce.

Our model is also amenable to a framework of investor decisions influenced by *anticipatory* emotions (Loewenstein, Weber, Hsee, and Welch (2001)).[6] The shocks in our model that shift preferences to irregular levels are exogenous but can be interpreted as external events coinciding with low consumption growth that induce fear in the market. For example, a terrorist attack or the perceived severity of a recession due to its portrayal in media coverage might induce fear in the market unrelated to the actual decline in consumption. This fear is an anticipatory emotion that immediately influences an investor's choice, inducing irregular preferences for risk and inter-temporal substitution in some states. However, investors have rational expectations and anticipate possible future fear states when making investment decisions today. Therefore, investors are "sophisticated" in the sense that they are aware that future states of fear will influence their contemporaneous decision in those future periods and take this into account in their optimal investment decision. In our model, this effect of anticipatory emotions on investor behavior will drive fluctuations in asset prices beyond traditional, fundamental risk factors. Periods of fear-induced irregular EIS and RA correspond to periods in which investors either pay "too much" for all assets ("excess frugality" motive) or pay "too much" for the risk-free asset to rebalance their portfolios ("excess safety" motive) *relative* to market fundamentals by accepting a lower and even negative return.[7] However, these returns are realized in an equilibrium that does not abandon investor rationality.

This behavioral interpretation of our model is consistent with evidence from Guiso et al.

[6]Loewenstein (2000, 1996) shows that visceral psychological factors such as fear can bypass the cognitive decision process and immediately influence an investor's decision. This contrasts to the traditional economic modeling view of *anticipated* emotions that are expected consequences of the decision rather than emotions experienced at the time of decision.

[7]We assume complete markets and the states of "excess frugality" and "excess savings" are fully anticipated under rational expectations, hence investors can fully hedge themselves against these states through a set of state-contingent claims that span the state space.

(2013) who repeatedly survey clients of an Italian bank before and after the 2008 financial crisis and find empirical evidence for substantially increased risk aversion after the crisis. They find that this increase in risk aversion cannot be explained by the usual risk factors such as changes in wealth, consumption habits, background risk or investor expectations. The authors then test the hypothesis that visceral psychological factors such as fear might be driving this change and give experimental evidence that a fear based explanation is consistent with their survey results. Cohn et al. (2013) also provide experimental results indicating that fear decreases an investor's willingness to take risks even if the fear is completely unrelated to economic events.

Our model most closely resembles that of Melino and Yang (2003), which is nested as a special case. Table 4 of Melino and Yang (2003) reports several combinations of parameter values that allow their model to match the first two moments of the risk-free rate and equity returns exactly with values of risk aversion ranging from 19.91 to 52.89. In response Donaldson and Mehra (2008) point out: "The reader may judge for herself whether any of the reported combinations constitute a reasonable resolution of the equity premium and associated puzzles. We venture only to comment that, for all cases, the degree of risk aversion implied by the low growth state seems high, especially in a context where the probability that the low growth state will continue for more than one period is less than 50 percent."[8]

However, we depart from the Melino and Yang (2003) setup in three important ways that allow us to match more stylized facts with a reasonable calibration for risk aversion. First, they impose perfect correlation between preference parameters and consumption growth which we break by allowing co-movement between consumption growth and preference parameters to occur with some probability. Second, in their model RA and the EIS always change together whereas we allow states where each, neither or both change. Lastly, the

[8] Donaldson and Mehra (2008), page 55.

frequency of preference parameter changes in their model is tied directly to the persistence in consumption growth and occurs 50% of the time. In contrast, our model is calibrated for very small transition probabilities, allowing for rare time-variation in preference parameters.

Our model contributes to the literature in several ways. First, with a parsimonious model that nests Mehra and Prescott (1985) as a special case, we are able to simultaneously generate many regularities of U.S. asset prices that have been historically difficult for consumption-based asset pricing models to produce. Second, the model captures an additional source of risk unrelated to consumption risk per se: fluctuations in preferences for smoothing consumption. This "smoothing risk" affects an investor's *ability to plan* consumption over long horizons, whereas consumption risk only affects an investor's *ability to smooth*, conditional on having a particular preference for smoothing. Third, while previous models have disentangled the effects of RA and the EIS on asset prices using Epstein and Zin (1989) preferences, our model disentangles the effect of *time-variation* in RA and the EIS on asset prices. Our model shows that time-varying EIS is more important than time-varying RA for many features of asset prices in the data, although time-varying RA can sharpen the overall fit.[9] This relationship is evident from the model's reliance on time-varying EIS to resolve the risk-free rate puzzle, generate an upward sloping real yield curve and generate the predictability results for consumption growth and lagged consumption growth—results not achieved with time-varying risk aversion alone. Fourth, the model provides additional quantitative motivation for future theoretical and empirical research on time-variation in preferences, especially time-varying EIS, which has received less attention in the literature. Finally, our model provides a theoretical framework that is consistent with recent empirical studies indicating that investor preferences can change for reasons unrelated to standard fundamental risk factors like changes in wealth, income risk, or consumption habit. This

[9] Melino and Yang (2003) come to a similar conclusion that time-varying EIS matters more than time-varying RA or a time-varying time discount factor for matching the first two moments of returns. Guvenen (2009) concludes that heterogeneity in the EIS and not in risk aversion is essential to improve the classic real business cycle model's poor asset pricing implications. Kamstra et al. (2014) show seasonal variation in the EIS parameter is important for matching seasonality in equity and Treasury returns.

feature is something that the traditional consumption-based asset pricing literature, which assumes marginal utility is driven exclusively by consumption innovations, is unable to do.

The remainder of the paper proceeds as follows. Section 1.2 describes the model economy; describes the joint Markov process for preference parameters and consumption growth; and derives the equilibrium stochastic discount factor. Section 1.3 presents the baseline calibration and several alternative calibrations of the model. Section 1.4 presents the model implications for matching asset pricing moments, predictability results, risk premium variation and the real term structure under the baseline and alternative calibrations. Section 1.5 presents a behavioral interpretation of the model results, defines the excess frugality and excess safety motives and discusses how they are related to discount factors, returns and the equity premium while Section 1.6 concludes.

1.2 The Model

1.2.1 Economy

We model a closed economy populated by a continuum of identical, infinitely-lived investors with no idiosyncratic uncertainty in individual endowments. Output in the economy is a homogenous good that is completely perishable as in the Lucas (1978) endowment economy. There is a single, non-durable consumption good C_t with supply $C = (C_t)_{t=0}^{\infty}$ and equity is a claim to the endowment process $(Y_t)_{t=0}^{\infty}$, the only asset held in non-zero net supply.

1.2.2 Endowment Process

In order to be able to cleanly discuss any potential gains achieved by relaxing the constant preference parameters assumption, we choose to model consumption dynamics as simply as possible. One immediate consequence of this choice is that our model, by construction, cannot say anything about variance ratios or predictability of consumption volatility by stock prices. However we gain the ability to isolate preference channels from other potential dynamics and the ability to solve the model analytically. This parsimonious setup is coarse, and in tying our hands with such simple consumption dynamics the fact that the model is able to do as well as it does with fewer degrees of freedom is quite surprising. We specify the stochastic process for the agent's endowment as in Mehra and Prescott (1985). Let Y_t be the aggregate endowment of the representative investor and suppose $(Y_t)_{t=0}^{\infty}$ follows the stochastic process

$$Y_{t+1} = \lambda_{Y,t+1} Y_t.$$

In the model economy, the aggregate endowment is equal to aggregate consumption in equilibrium, hence $\lambda_{Y,t+1} = G_{t+1}$. Now suppose the growth rate of consumption process $(G_t)_{t=0}^{\infty}$ is a finite-state time-homogeneous Markov process on the following two states

$$g_h = \mu_c + \sigma,$$
$$g_l = \mu_c - \sigma,$$

where g_h and g_l indicate high and low consumption growth states. Here, μ_c is the mean and σ the standard deviation for G_{t+1}. The transition probabilities are given by

$$P[G_{t+1} = g_h | G_t = g_h] = P[G_{t+1} = g_l | G_t = g_l] = \frac{1+\rho}{2},$$
$$P[G_{t+1} = g_h | G_t = g_l] = P[G_{t+1} = g_l | G_t = g_h] = \frac{1-\rho}{2},$$

where ρ indicates the persistence of the consumption growth process. As is commonly done in endowment economy asset-pricing models, we specify a scaled consumption process for dividends that accounts for the fact that the volatility of dividend and consumption growth can, in general, be different due to leveraging.[10] Therefore, we specify the growth rate of

[10] See for example, Campbell (1986, 2003), Abel (1999), Lettau, Ludvigson, and Wachter (2008) and Wachter (2013))

dividends $(D_t)_{t=0}^{\infty}$ as following the stochastic process

$$
\begin{aligned}
D_{t+1} &= \lambda_{D,t+1} D_t, \\
\lambda_{D,t} &= \mu_D + \phi_D (G_t - \mu_c),
\end{aligned} \tag{1.1}
$$

where μ_D is the mean of dividend growth and ϕ_D is the dividend leverage parameter.

1.2.3 Preferences

Individual preferences in this economy are defined recursively over current consumption as in Epstein and Zin (1989) with the modification that the coefficient of relative risk aversion γ_t and the elasticity of inter-temporal substitution (EIS) parameter ψ_t are allowed to vary over time. Individuals investors choose c_t, however, since they are identical and we assume there is no idiosyncratic uncertainty in individual endowments, we can price assets in this economy by solving the following representative agent's choice of aggregate consumption C_t and asset holdings h_t according to

$$
V_t(W_t) = \max_{\{C_t, h_t\}} \left[C_t^{\frac{1-\gamma_t}{\theta_t}} + \delta \left(\mathbf{E}_t \left[V_{t+1}(W_{t+1})^{1-\gamma_t} \right] \right)^{\frac{1}{\theta_t}} \right]^{\frac{\theta_t}{1-\gamma_t}}
$$

subject to the period budget constraint

$$
C_t + P_t' h_{t+1} = d_t' h_t + P_t' h_t \equiv W_t
$$

where $\theta_t \equiv \frac{1-\gamma_t}{1-\frac{1}{\psi_t}}$; P_t refers to a $n \times 1$ vector of asset prices per share at date t that offers a real dividend stream of d_{t+j}, a $n \times 1$ vector with $j = (1, \ldots, \infty)$; and h_t is a $n \times 1$ vector of asset holdings at the end of period $t-1$, which includes the risk-free asset.

1.2.4 Model Dynamics

Discrete State Joint Markov Process

Let $(s_t)_{t=0}^{\infty} \equiv (G_t, \gamma_t, \psi_t)_{t=0}^{\infty}$ be a joint stochastic process that captures the state of consumption growth, risk aversion and the EIS parameter. Investors in the model have rational expectations so they know the equilibrium aggregate growth rate will be G_t at time t. However, since an individual investor is of measure zero, an investor's choice of c_t is "external" to the state variable s_t.[11] That is, at time t, aggregate consumption growth G_t and preference parameters γ_t and ψ_t are exogenous to an individual investor's choice of c_t.

Suppose that at time t consumption growth, risk aversion and the EIS parameter can each realize one of two possible states $G_t = \{g_\ell, g_h\}$, $\gamma_t = \{\gamma_0, \gamma_{\text{elev}}\}$ and $\psi_t = \{\psi_0, \psi_{\text{depr}}\}$ where (γ_0, ψ_0) are the "regular" values of risk aversion and the EIS parameter while $(\gamma_{\text{elev}}, \psi_{\text{depr}})$ represent "irregular" preferences, driven by an exogenous shock, where risk aversion is elevated from its regular level γ_0 and the EIS parameter is depressed from its regular level ψ_0. We use the term "irregular" here in its literal sense: contrary to what is normal and do not wish to invoke the imagery of irrationality or mistaken preferences. Furthermore, it should be noted that changes in γ_t and ψ_t are not permanent structural breaks in investor preferences. Rather, they are temporary, anticipated by investors with rational expectations and expected to revert to their regular values.

Suppose that s_t evolves according to a finite-state, time-homogenous Markov process over

[11] We use the notion of "external" in the same way it is used in the external habits models of Abel (1990) and Campbell and Cochrane (1999).

the states:

$$
\begin{aligned}
s_1 &: \ (g_h, \gamma_0, \psi_0) \\
s_2 &: \ (g_\ell, \gamma_0, \psi_0) \\
s_3 &: \ (g_\ell, \gamma_{\text{elev}}, \psi_0) \\
s_4 &: \ (g_\ell, \gamma_0, \psi_{\text{depr}}) \\
s_5 &: \ (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}}) \\
s_6 &: \ (g_h, \gamma_{\text{elev}}, \psi_0) \\
s_7 &: \ (g_h, \gamma_0, \psi_{\text{depr}}) \\
s_8 &: \ (g_h, \gamma_{\text{elev}}, \psi_{\text{depr}}).
\end{aligned}
$$

The states $\{s_1, s_2\}$ are those where preferences are at their regular values and do not change with the state of consumption growth. Guiso et al. (2013) and Cohn et al. (2013) provide empirical evidence for counter-cyclical risk aversion while Melino and Yang (2003) find counter-cyclical risk aversion necessary to match the first two moments of asset prices, so we impose this assumption in our model by restricting $\gamma_0 < \gamma_{\text{elev}}$ and disregarding states $\{s_6, s_8\}$. Crossley and Low (2011) show that the EIS is not constant over time, although, to the best of our knowledge there are no empirical studies to date regarding the direction of its cyclicality with the business cycle. However, Melino and Yang (2003) find a pro-cyclical EIS parameter is necessary for their model to match the first two moments of asset prices, so we impose this assumption by restricting $\psi_0 > \psi_{\text{depr}}$ and disregarding state s_7.

State Space Transition Matrix

Given our assumptions that risk aversion is counter-cyclical and the EIS parameter is pro-cyclical, we restrict the state space to be $S = \{s_1, s_2, s_3, s_4, s_5\}$. We specify the transition matrix $\Pi_{t,t+1}$ that governs the joint Markov process of consumption growth and preferences as

$$
\begin{array}{cc}
 & \begin{array}{ccccc} (g_h, \gamma_0, \psi_0) & (g_\ell, \gamma_0, \psi_0) & (g_\ell, \gamma_{\text{elev}}, \psi_0) & (g_\ell, \gamma_0, \psi_{\text{depr}}) & (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}}) \end{array} \\
\begin{array}{c} (g_h, \gamma_0, \psi_0) \\ (g_\ell, \gamma_0, \psi_0) \\ (g_\ell, \gamma_{\text{elev}}, \psi_0) \\ (g_\ell, \gamma_0, \psi_{\text{depr}}) \\ (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}}) \end{array} &
\begin{pmatrix}
\frac{1+\rho}{2} & [1-(b(1-d)+d)]\left(\frac{1-\rho}{2}\right) & b(1-d)\left(\frac{1-\rho}{2}\right) & d(1-b)\left(\frac{1-\rho}{2}\right) & bd\left(\frac{1-\rho}{2}\right) \\
\frac{1-\rho}{2} & [1-(b(1-d)+d)]\left(\frac{1+\rho}{2}\right) & b(1-d)\left(\frac{1+\rho}{2}\right) & d(1-b)\left(\frac{1+\rho}{2}\right) & bd\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & (1-d)\left(\frac{1+\rho}{2}\right) & 0 & d\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & 0 & (1-b)\left(\frac{1+\rho}{2}\right) & b\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & 0 & 0 & \left(\frac{1+\rho}{2}\right)
\end{pmatrix}
\end{array},
\tag{1.2}
$$

where b is the conditional probability of transitioning from regular risk aversion (γ_0) into a state of elevated risk aversion (γ_{elev}) when an exogenous shock occurs that *coincides* with low consumption growth next period. In other words, when a period of low consumption growth occurs under regular risk aversion, the risk aversion will be elevated with probability b where

$$b = Pr\left[\gamma_{t+1} = \gamma_{\text{elev}} | \gamma_t = \gamma_0, G_{t+1} = g_\ell\right].$$

Similarly, d is the conditional probability of transitioning from a regular level of the EIS parameter (ψ_0) into a state where the EIS parameter is depressed (γ_{elev}) when an exogenous shock occurs that *coincides* with low consumption growth next period. In other words, when a period of low consumption growth occurs under the regular value of the EIS parameter, the EIS parameter will be depressed with probability d where

$$d = Pr\left[\psi_{t+1} = \psi_{\text{depr}} | \psi_t = \psi_0, G_{t+1} = g_\ell\right].$$

Recall that we want to retain the simple consumption dynamics of Mehra and Prescott (1985) in order to cleanly investigate whether relaxing the assumption of time-varying preferences buys us any ability to explain asset prices. Notice that the transition matrix preserves these dynamics:

$$Pr\{s_{t+1} = s_1 | s_t = s_1\} = Pr\{s_{t+1} \in \{s_2, s_3, s_4, s_5\} | s_t \in \{s_2, s_3, s_4, s_5\}\} = \frac{1+\rho}{2}$$
$$Pr\{s_{t+1} = s_1 | s_t \in \{s_2, s_3, s_4, s_5\}\} = Pr\{s_{t+1} \in \{s_2, s_3, s_4, s_5\} | s_t = s_1\} = \frac{1-\rho}{2}.$$

Our transition matrix also generalizes the Markov transition specifications of both Mehra and Prescott (1985) and Melino and Yang (2003). When $b = d = 0$ the transition matrix is equivalent to the one in Mehra and Prescott (1985). Furthermore, because we are using the same preference specification as in Melino and Yang (2003), their model is nested in ours for when $b = d = 1$. This nesting comes from the fact that they only model states $\{s_1, s_5\}$ and impose perfect correlation between preference parameters and consumption growth. In other words, their model is restricted so that preference parameters change *every time* realized consumption growth changes from its previous value.

Our model departs from the Melino and Yang (2003) setup in three important ways. First, we break this perfect correlation by allowing co-movement between consumption growth and preference parameters to occur with probabilities $0 < b < 1$ and $0 < d < 1$. This allows us to capture time-varying preferences and the desired cyclical relationship between consumption growth and preference parameters while also allowing the potential for realized states in which consumption growth transitions but preferences remain unchanged. Second, in their model, γ_t and ψ_t always change together and we allow states where either γ_t changes, ψ_t changes, or they both change. Finally, in Table 4 of Melino and Yang (2003) they report several combinations of parameter values that allow their model to match the first two moments of the risk-free rate and equity returns exactly with values of risk aversion ranging from 19.91 to 52.89 with *average* levels of risk aversion ranging from 10.12 to 26.02, which as Donaldson and Mehra (2008) suggest are too high and occur too frequently to seem plausible. This occurs in their model because the frequency of preference parameter changes is tied directly to the persistence in consumption growth and occurs 50% of the time.[12] Our generalization addresses these issues and our model is calibrated for very small values of b and d (shown below), allowing time variation in preference parameters but only requiring them to change very rarely and implying a more reasonable value of the average level of risk aversion.

1.2.5 Model Timing

The model timing goes as follows. At time t individual investors observe a realization of state variable $s_t = (G_t, \gamma_t, \psi_t)$, which contains all the information about the current state of the economy G_t. Since individual investors are of measure zero, consumption growth G_t and the preference parameters of the representative agent γ_t and ψ_t are exogenous to an individual investor's choice of c_t, which they choose at time t given s_t. This is what we mean by the individual investor's choice of c_t being external to the state variable s_t at time t. With some probability b or d an exogenous shock occurs at time t, coincidentally with the realization of G_t, resulting in a realization of state s_t where preference parameters are at irregular levels. If a shock occurs, since individual investors are of measure zero and have identical preferences, in equilibrium they will make their consumption choice given the irregular preference parameter values of the representative agent.

1.2.6 Equilibrium Pricing Equations

We solve the representative agent's problem and show in Appendix A.1 that the asset pricing restrictions on any arbitrary asset j with gross return $R_{j,t+1}$ satisfy the equilibrium condition

$$\mathbf{E}_t[M_{t+1} \cdot R_{j,t+1}] = 1$$

[12] For instance, in an annual data sample of 84 years, their model restricts γ_t and ψ_t to both change 42 of those years.

where

$$M_{t+1} = \delta^{\theta_t} Z_{a,t}^{1-\theta_t} G_{t+1}^{-\gamma_t} (Z_{a,t+1} + 1)^{\zeta_{t,t+1}-1} \tag{1.3}$$

is the stochastic discount factor (SDF), $G_t = \frac{C_t}{C_{t-1}}$ is aggregate consumption growth and $Z_{a,t}$ is the price-dividend ratio for the *unobservable* asset with gross return $R_{a,t+1}$ that pays aggregate consumption as a dividend given by

$$Z_{a,t} = \delta \left(\mathbf{E}_t \left[G_{t+1}^{1-\gamma_t} (Z_{a,t+1} + 1)^{\zeta_{t,t+1}} \right] \right)^{\frac{1}{\theta_t}} . \tag{1.4}$$

The parameter θ_t is defined as before while $\zeta_{t,t+1} \equiv \frac{1-\gamma_t}{1-\frac{1}{\psi_{t+1}}}$. All sources of risk in this economy will be generated by innovations in the equilibrium SDF in Equation (1.3). However, a closed form expression for these innovations is not available without further assumptions due to the fact that the SDF is non-linear in the state variable s_t and the fact that $Z_{a,t}$ is a recursive, non-linear function of s_t. To avoid this type of difficulty, researchers will typically make simplifying assumptions such as assuming $Z_{a,t}$ is linear in certain state variables or log-linearizing the SDF. The advantage of our parsimonious setup is that it is relatively straightforward to solve these equations exactly. This allows the model to produce exact population values for all the moments we are interested in rather than relying on simulation. We can gain insight into the structure of these risks by looking at an equivalent expression for the equilibrium SDF in Equation (1.3), which we derive in Appendix A.2,

$$M_{t+1} = M_{t+1}^{ez}(\gamma_t, \psi_t) \cdot (Z_{a,t+1} + 1)^{\zeta_{t,t+1}-\theta_t} \tag{1.5}$$

where $M_{t+1}^{ez}(\gamma, \psi) \equiv \delta^{\theta} G_{t+1}^{-\frac{\theta}{\psi}} R_{a,t+1}^{-(1-\theta)}$ is the equilibrium stochastic discount factor under the standard Epstein and Zin (1989) preferences. Taking logs of Equation (1.5) gives

$$m_{t+1} = m_{t+1}^{ez}(\gamma_t, \psi_t) + (\zeta_{t,t+1} - \theta_t) \cdot \ln(Z_{a,t+1} + 1) \tag{1.6}$$

where lower case m's denote the log values of their M counterparts and define

$$sr_{t+1} \equiv (\zeta_{t,t+1} - \theta_t) \cdot \ln(Z_{a,t+1} + 1).$$

Finally, it can be shown by straightforward algebra that

$$\zeta_{t,t+1} - \theta_t = (\gamma_t - 1) \left(\frac{\psi_{t+1} - \psi_t}{(\psi_{t+1} - 1)(\psi_t - 1)} \right).$$

The discussion that follows is meant to guide the intuition of the model's results and should be taken as illustrative given the fact that Equation (1.5) is nonlinear in the state variable s_t.

1.2.7 Smoothing Risk

Since consumption growth and preference parameters are the only sources of stochastic fluctuations in our model, Equation (1.6) implies that innovations in m_{t+1} come through two channels. The first channel is the usual innovations in consumption growth under the standard Epstein and Zin (1989) stochastic discount factor m^{ez}_{t+1} with the modification that the market price of this risk, which is a function of preference parameters, will be amplified by fluctuations in preference parameters γ_t and ψ_t.[13] However, there is an additional source of risk coming from innovations in sr_{t+1}. First, consider what happens if we shut down time-variation in the EIS parameter so that only risk-aversion is time varying, then $\zeta_{t,t+1} = \theta_t$ so that $sr_{t+1} = 0$. This results in an SDF that gives the same pricing implications as the standard recursive preference model although investors are willing to pay a much higher premium for assets that pay them off in a recession state with elevated risk aversion versus the premium they will pay for claims in a regular recession: the usual market price of consumption growth risk associated with innovations in m^{ez}_{t+1} are scaled up when γ_t is

[13]For instance, in the model of Bansal and Yaron (2004), the market price of risk for innovations in consumption growth is given by $\lambda_{m,\eta} = \left(-\frac{\theta}{\psi} + \theta - 1\right)$.

large because it is counter-cyclical.

However, consider shutting down time variation in risk aversion but allowing the EIS parameter to be time varying. Then from Equation (1.6) we see that sr_{t+1} will either increase or decrease the marginal utility relative to the standard recursive utility model depending on which states are being transitioned into.[14] From this expression, it is clear that if the economy is transitioning into a state where the EIS parameter is depressed, then $\psi_t > \psi_{t+1}$ and since $\gamma > 1$ we have $\zeta_{t+1} - \theta_t < 0$, which implies $sr_{t+1} < 0$. Alternatively, if the economy is transitioning from a state where the EIS parameter is depressed to a state of regular preferences then $sr_{t+1} > 0$. If both parameters are allowed to vary over time, risk aversion will amplify the magnitude of sr_{t+1} because γ_t itself enters the expression $\zeta_{t,t+1} - \theta_t$ as a scale factor.[15]

This identifies an additional risk channel in this economy that comes from innovations in sr_{t+1}, which are due to fluctuations in investor's preferences for inter-temporal substitution. This new risk channel we call "smoothing risk" and it operates through investors' uncertainty about their preference for how much they should consume today versus save for the future. That is, there is some uncertainty about what the investor's optimal lifetime consumption profile should look like when making consumption and savings decisions at time t that inhibits the investor's *ability to plan* for future periods. This risk channel is distinct from the usual consumption risk channel that affects the investor's *ability to smooth* consumption conditional on having a particular preference for consumption smoothing. Of course, because $Z_{a,t+1}$ is itself a function of G_{t+1}, γ_t and ψ_t we are unable to determine a priori from the functional form of Equation (1.5) if the consumption risk or smoothing risk is more important for equilibrium asset prices. Fortunately, the exact solution of our model

[14] We also have the standard market prices of risk being time-varying and scaled by the value of ψ_t as in the case when only RA is time-varying.

[15] However, the overall effect on marginal utility is unclear due to the non-linear function $Z_{a,t}$ being a function of s_t.

allows us to investigate this further by testing the sensitivity of the equilibrium SDF for each of these risks, which we discuss in Section 1.4.1

1.2.8 Elasticity of Intertemporal Substitution

The previous section demonstrated that fluctuations in the parameter ψ_t generate a new source of risk for asset prices. Up to this point, we have taken great care in referring to ψ_t as the EIS *parameter* and not simply as "the EIS." In models where the parameter ψ is not time-varying, this is indeed the EIS. However, as Melino and Yang (2003) show, when ψ is allowed to be time-varying with recursive preferences, the EIS is not simply just the parameter ψ_t, it takes the following form:

$$EIS_{t,t+1} = \frac{1 + M_{t+1}G_{t+1}}{\frac{1}{\psi_t}(1 + M_{t+1}G_{t+1}) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)}, \tag{1.7}$$

where M_{t+1} is the stochastic discount factor and $G_{t+1} = \frac{C_{t+1}}{C_t}$ is aggregate consumption growth. The assumption we make restricting the transition matrix by only allowing preferences to revert to normal when high consumption growth is realized is sufficient to ensure that pro-cyclicality in the EIS parameter ψ_t implies the EIS is also pro-cyclical. This is stated formally in the following lemma

Lemma 1. *If the discrete state, joint Markov process of $s_t = (G_t, \gamma_t, \psi_t)$ is restricted over states $S = \{s_1, s_2, s_3, s_4, s_5\}$ so that preferences do not revert from irregular (γ_{elev} or ψ_{depr}) to regular (γ_0 or ψ_0) states until high consumption growth is realized, then pro-cyclicality of the EIS parameter ψ_t implies that $EIS_{t,t+1}$ (as given by Equation (1.7)) is pro-cyclical.*

The proof of this lemma is given in Appendix A.5. In light of this, in the discussion that follows regarding how the cyclicality of the EIS is related to asset prices, we will refer to the EIS parameter ψ_t and the EIS given by Equation (1.7) interchangeably.

Given that rare fluctuations in the EIS generate a new source of risk crucial for many of the model's results, it is useful to discuss what the EIS is and what it means for the EIS to be time-varying. Researchers often refer to the EIS in different ways. Two of the most common ways are as consumption (savings) sensitivity to changes in interest rates and as a preference for consumption smoothing. In general, the elasticity of inter-temporal substitution is approximately defined to be

$$EIS \approx \frac{\partial \ln(c_{t+1}/c_t)}{\partial r}, \tag{1.8}$$

a percent change in consumption growth per percent increase in the net interest rate. Suppose two investors A and B have preferences for inter-temporal substitution such that $EIS_A < EIS_B$.[16] In terms of an elasticity, investor A's consumption choice is *less* sensitive to changes in the interest rate than investor B's choice. This is another way of saying that investor A has a *stronger preference for consumption smoothing* than investor B.

To see why a lower EIS implies a stronger preference for consumption smoothing, take the extreme case of investor A preferring a completely smooth consumption profile. This preference implies that $\partial \ln(c_{t+1}/c_t)$ is constant. Then Equation (1.8) implies that if investors A observes a large change in interest rates and she prefers to keep $\partial \ln(c_{t+1}/c_t)$ constant through her consumption choice, she must have a low EIS and lower than B who has a weaker preference for consumption smoothing. We can think of A and B as the same investor over two different time periods, with future-self A having a stronger preference for consumption smoothing than present-self B.

Finally, to assist our intuition on what it means for the EIS to vary over time, it is useful to understand how it is different from investor risk aversion. The investor's level of risk

[16] In an endowment economy, since the entire endowment is consumed in equilibrium, talking about the sensitivity of investor consumption choice versus the growth rate of consumption relative to changes in interest rates is equivalent since the former determines the latter.

aversion measures how averse an investor is at time t to variation in consumption *across different states* at time $t+1$. Whereas the EIS measures how averse an investor is at time t to consumption variation *across future time periods* along a deterministic path of consumption. The EIS changing over time implies that there are periods when an investor is more or less averse to fluctuations in consumption across time. In this way we can think of the smoothing risk, associated with the EIS changing over time, as affecting an investor's ability to plan their consumption profile over long horizons.

1.2.9 Discussion

We do not explicitly model the shocks that drive changes in γ_t and ψ_t, they are taken to be exogenous to the model. This simplifying assumption allows the model to be agnostic to the stochastic process that is driving changes in preference parameters. However, we present the following as one plausible behavioral interpretation for why preferences might be time-varying that is consistent with the evidence presented in Guiso et al. (2013) and Cohn et al. (2013): preferences are at their regular levels (γ_0, ψ_0) most of the time, however, on rare occasion an exogenous shock that *coincides* with low consumption growth induces a psychological reaction — such as fear — in individuals, which changes their appetite for risk and/or their desire to smooth consumption across periods to irregular levels.

Under this behavioral interpretation, since the state s_t is taken as given at the time of the investment decision, when fear induces a particular state s_t it is an *anticipatory* emotion (Loewenstein et al. (2001)) that investors experience at the time they make their decisions. Hence, this visceral psychological factor (Loewenstein (1996, 2000)) can bypass the cognitive decision process and immediately influence an investor's decision. This is in contrast to the traditional economic modeling view of *anticipated* emotions that are expected consequences of the decision (e.g. regret or disappointment) rather than emotions experienced at the time of decision. However, investors in our model have rational expectations and anticipate possible future fear states when making investment decisions today. Furthermore, investors are *sophisticated* in the sense that they know that future states of fear will influence their contemporaneous decision in those future periods and they take this into account when making their optimal investment decision. Therefore, there is no dynamic inconsistency in the model because investors have rational expectations and take into account the fact that there might be rare future periods when their preferences will be irregular, due to some fear inducing shock.

Given this interpretation, states $\{s_3, s_4, s_5\}$ can be thought of as "fear states" under which consumption growth is low and preferences are at irregular levels. While $\{s_1, s_2\}$ are states with preferences at regular levels and invariant to whether high or low consumption growth is realized. In our model, the EIS is pro-cyclical so that when low consumption growth is realized in a fear state, the EIS decreases from its regular level to its irregular level. This implies when the economy is in a fear state—relative to a regular state of the economy—investors are less sensitive to changes in the interest rate and have a stronger preferences for consumption smoothing. Likewise, since risk aversion in counter-cyclical, when the economy is in a fear state investors are more risk averse relative to regular states of the economy. It is important to note that this behavioral interpretation merely provides a plausible explanation for the source of variation in preference parameters (that is not being explicitly modeled) that is, in part, driving fluctuations in equilibrium asset prices in the model.

With this in mind, there are a few modeling assumptions that are reflected in the structure of the transition matrix. First, we assume that the probabilities b and d are independent, an assumption made simply for modeling parsimony. Second, and more importantly, we do not allow the state to revert from a fear state with irregular preferences (γ_{elev} or ψ_{depr}) to states with regular preferences (γ_0 or ψ_0) before consumption growth is high again. That is, if investors are in a fear state, we assume that realized high consumption growth is taken to be good news, which assuages investors fears and shifts their preferences back to regular levels. The second assumption we make on the transition matrix might seem arbitrary, especially abstracted from this behavioral interpretation. However, we did not set out with the intent to match asset pricing moments and then back out the necessary restrictions on the transition matrix to make the model work.[17] Rather, we had this behavioral interpretation in mind and constructed a transition matrix that is consistent with this view of what might be driving preferences to vary over time.

The state space of our model also assumes that preference changes coincide with some recessions and not with others. Malmendier and Nagel (2011) and Guiso et al. (2013) document evidence that the Great Depression and Great Recession were associated with changes in investor risk aversion. Of course, these studies just provide evidence for preference changes coinciding with recessions but we cannot infer from them that there are recessions in the U.S. data that *do not* coincide with preferences changing nor do they say anything about the preference for consumption smoothing changing. One plausible explanation for the EIS changing in some recessions and not in others is if the recession induces uncertainty about the value of a long-term asset or the long-term path of the economy. For instance, two recessions might look identical in terms of the observed decline in *aggregate* consumption. However, suppose one is driven by all sectors being negatively affected by the same amount while the other recession was driven by a particularly large decline in a sector like housing or technology (the Dot Com bubble). Unprecedented or un-anticipated events that generate uncertainty about consumption over the long-run can cause agents to re-evaluate everything, possibly affecting their preferences to be more averse to consumption fluctuations going forward.[18]

[17]Indeed, this might just be one of many transition matrix specifications that could potentially result in the model matching the data.

[18]Most models of the housing market assumed no aggregate drop in prices since no aggregate price drop had been observed in the data prior to the 2008 financial crisis.

A different explanation, that is consistent with the behavioral interpretation given above, is that fear might be the reason an investor's preference for consumption smoothing changes in some recessions and not others. For instance, if a recession coincides with an event like a terrorist attack, this attack could induce fear about the long-term implications of the attack on the economy. Likewise, if a recession is accompanied by a lot of negative media coverage, this could induce fear as people perceive the recession to be much worse than it actually is in terms of the economic fundamentals. The key is that the observed consumption decline could be the same in a recession that coincided with a terrorist attack, a lot of negative media coverage or neither. Therefore, one way to think of the effect of fear on investor preferences is that fear induces a preference for consumption rationing. That is, investors prefer to have a stable and smooth consumption profile in the face of fear induced uncertainty about the long-term path of the economy that is unrelated to market fundamentals.

1.3 Model Calibration

In order to derive the asset pricing implications from the model outlined in the previous section, we calibrate aggregate consumption and dividend growth dynamics to annual U.S. data from 1930-2013. Details on the data used for the calibration are provided in Appendix A.3. Our baseline calibration is reported in Table 1, along with alternative calibrations for a few special cases to be discussed in subsequent sections. The dividend leverage parameter is chosen to be 4.5, which is a bit higher than the value used by others, but the same value as used in Lettau et al. (2008).[19] Furthermore, this choice of calibration results in a model implied value for the standard deviation of dividends that is within the 95% confidence interval from the data estimate over our sample as reported in Table 2. We also calibrate the conditional probabilities b and d in the transition matrix to 5% and 12.5% respectively.

[19] For example, Abel (1999) uses 2.74 while Bansal and Yaron (2004) use 3. However, unlike here, these models assume lognormal returns so the values are not directly comparable.

Recall the regular (γ_0, ψ_0) and irregular ($\gamma_{\text{elev}}, \psi_{\text{depr}}$) preference parameters. We define the parameter k_γ to be the elevated risk aversion factor where $\gamma_{\text{elev}} = \gamma_0 k_\gamma$ and k_ψ to be the depressed EIS offset where $\psi_{\text{depr}} = \psi_0 - k_\psi$. The model calibration implies a constant regular level of risk aversion of 7.25 for the vast majority of time periods. However, on rare occasion ($b = 0.05$) an exogenous shock elevates investor risk aversion by a factor of $k_\gamma = 3.24$ times the regular level. This calibration is consistent with the empirical evidence presented in Guiso et al. (2013) who estimate that after the 2008 financial crisis, risk aversion increased 2.0-3.5 times the pre-crisis level.[20] Mehra and Prescott (1985) argue that a value of 10 for risk aversion is the maximum feasible value, a rule of thumb often invoked in the asset pricing literature using the class of representative agent preferences. In our baseline calibration, in the majority of periods, we require a value for risk aversion of only 7.25. However, the elevated value for risk aversion is $\gamma_{\text{elev}} = \gamma_0 k_\gamma = 23.5$, which is high but still much lower than, for example, the risk aversion of about 80 implied by Campbell and Cochrane (1999) when consumption surplus is at its steady state (and in the hundreds for low-consumption surplus ratios, which correspond with"recessions") and in the low-end of the range for this parameter reported in Table 4 of Melino and Yang (2003). Furthermore, risk aversion is rarely this high in our model, elevated by the plausible factor of 3.24 only once every 42 years on average and then reverting to its regular level in under four years on average. If preference parameters, such as risk aversion, actually vary over time then prior estimates of risk aversion from the data are estimates of the *mean* level of a random variable. In the bottom panel of Table 1 we report the model implied unconditional means of γ_t and ψ_t. Under this interpretation of previous acceptable benchmark values of risk aversion being the mean of a random variable, our model requires $\mathbf{E}[\gamma_t]$ to be 8.60, which is less than the plausible maximum benchmark of 10.

[20]They estimate a change in risk aversion by a factor of 2 for the average investor in their data and 3.5 for the median investor.

We also calibrate the regular level of the EIS parameter to be 0.956. The "correct" value of the EIS is widely debated and there is an extensive empirical literature that attempts to estimate it with estimates ranging from very small (even negative) to larger than one.[21] In our calibration, we did not set out with a particular value for this parameter in mind, however, our model matches more regularities of asset prices with the EIS parameter at just below one ($\mathbf{E}[\psi_t] = 0.9556$), which implies a preference for early resolution of uncertainty since $1/EIS_{t,t+1} < \gamma_t$ in all states of our model. In the end, among other consumption based asset pricing models in the literature, our calibration of ψ_t fits right between the small values of around 0.1-0.3 (Campbell and Cochrane (1999) and Guvenen (2009)) and the larger values of 1.0-1.5 (Wachter (2013), Bansal and Yaron (2004) and Bansal et al. (2012)).

The calibrated level of the EIS parameter is 0.956 for the vast majority of years, however, on rare occasions ($d = 0.125$) an exogenous shock depresses the EIS parameter by $k_\psi = 0.002$. It may seem striking that our calibration only requires such a small movement in the EIS parameter. Since we have little empirical guidance on plausible variation in the EIS, small movements are a conservative assumption. Moreover, given the difficulty in statistical estimation of the EIS in the literature under the assumption of constant EIS, the small movement in our calibration is very likely not to be rejected by statistical test. However, this magnitude is in the range of values that Kamstra et al. (2014) require in seasonal fluctuation of the EIS parameter. Also, the magnitude of k_ψ implies a 20 basis point change in the *sensitivity* of consumption growth to a change in interest rates, which does not strike us as implausibly small. The probability b in the baseline calibration implies

[21] Havranek, Horvath, Irsova, and Rusnak (2013) provides a recent broad survey of estimates across multiple studies and countries and show a wide variation in estimates. Campbell (1999) reports widely varying and often imprecise estimates. Hall (1988), Vissing-Jorgensen (2002) and Guren, Manoli, Weber, and Chetty (2011) estimate EIS to be small (around zero or less than one). While Hansen and Singleton (1982), Attanasio and Weber (1989), Beaudry and Wincoop (1996), Gruber (2006) and Engegelhardt and Kumar (2009) estimate the EIS to be large (around one or greater than one). Guren et al. (2011) provides a good survey on the various estimates of the EIS and how these estimates vary depending on if they are micro or macro estimates.

that risk aversion transitions into an irregular state about once every 42 years, with an average duration of irregular risk aversion of about 3.8 years. Likewise, the probability d in the baseline calibration implies that the EIS parameter transitions into an irregular state about once every 18 years, with an average duration of about 3.8 years. If we assume the Great Depression and the Great Recession were periods of low consumption growth that corresponded with a state of fear shifting investor preferences, then our baseline calibration is roughly consistent with the frequency and duration of these states of the U.S. economy over the sample period 1930-2013.[22]

Before discussing the model's ability to match the stylized facts of aggregate asset prices, it is important to note the number of degrees of freedom our model exhibits. Of all the parameters in Table 1, only the discount factor (δ), the regular values of risk aversion and the EIS parameter (γ_0, ψ_0), the depressed EIS parameter offset (k_ψ) and the conditional probabilities (b, d) are not calibrated directly to data or from empirical evidence. However, the EIS parameter offset is very small, which would not obviously amplify the results of the model a priori. Furthermore, b and d are closely tied to the average levels of RA and EIS generated by the model, and those levels were targeted under the constraints that the relevant literature implies a plausible risk aversion be less that 10 and estimates of the EIS to be somewhere between 0 and 2. Hence, we only have six degrees of freedom in calibrating our model. Given this feature, coupled with the fact that we assume very simple consumption and dividend dynamics with a very coarse state space, it is actually quite surprising the model does well in producing as large a number of asset price features as it does, lending credibility to the model's basic insights.

[22]This assumption is consistent with the empirical studies of Malmendier and Nagel (2011) and Guiso et al. (2013) documenting evidence that these periods were associated with changes in investor preferences.

1.4 Model Implications and Results

1.4.1 Equilibrium Discount Factors

The stochastic discount factor in Equation (1.5) is highly nonlinear because $Z_{a,t+1}$ will be a recursive function of the model primitives, including the state variable s_t. As a result, we do not have closed-form expressions for innovations in the SDF. However, our parsimonious setup allows us to solve the model exactly without invoking a log-linear approximation and simulation, which means we can look at the state contingent SDF being generated directly from the model. Step by step details of our numerical solution method are outlined in Appendix A.4. Let M denote the equilibrium stochastic discount factor generated by the model where each row and column corresponds to one of the model's five states at time t and $t+1$ respectively. Under our baseline calibration, we obtain:

$$M_{t,t+1} = \begin{array}{c c} & \begin{array}{ccccc} s_1 & s_2 & s_3 & s_4 & s_5 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \begin{pmatrix} 0.83 & 1.38 & 2.63 & 0.52 & 0.54 \\ 0.68 & 1.13 & 2.15 & 0.42 & 0.44 \\ 0.03 & . & 1.53 & . & 0.01 \\ 1.46 & . & . & 0.92 & 0.96 \\ 2.08 & . & . & . & 0.73 \end{pmatrix} \end{array}. \tag{1.9}$$

Recall the five states of the model:

$$\{s_1, s_2, s_3, s_4, s_5\} = \{(g_h, \gamma_0, \psi_0), (g_\ell, \gamma_0, \psi_0), (g_\ell, \gamma_{\text{elev}}, \psi_0), (g_\ell, \gamma_0, \psi_{\text{depr}}), (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}})\}.$$

In consumption-based asset pricing models, the equilibrium discount factor has a direct relationship with investor marginal utility as discount factors for state contingent claims in a complete market will reflect the relative marginal utility the investor faces in each possible state of the world. More precisely, investors will pay a premium for state contingent assets that insure them against bad states of the world that pay them when marginal utility is high. Likewise, investors will demand a discount for state contingent assets that pay them in good states of the world when marginal utility is low. Looking at Matrix (1.9), in times of regular preferences, and in recessions with only elevated risk aversion (state transition paths between s_1, s_2 and s_3), discount factors behave as expected under the standard model. Investors are willing to pay a premium (1.38, 1.13, 2.63, 2.15, 1.53) and demand a discount (0.83, 0.68, 0.03) for a claim in an expansion when marginal utility is low with the premiums and discounts being higher under elevated risk aversion.

However, in recessions with a depressed EIS parameter, the SDF seems to price assets counter to the standard model with discounts demanded to hold contingent claims paying off in states s_4 and s_5 when consumption growth is low. Although this result may seem counterintuitive, it turns out that it is not because investors in the model consider states s_4 and s_5 to be states of *low* marginal utility from the perspective of time t, even though consumption growth is low. To see why, we will compare states $s_2 = (g_\ell, \gamma_0, \psi_0)$ and $s_4 = (g_\ell, \gamma_0, \psi_{\text{depr}})$ that differ only in that s_4 is a state of depressed EIS. Recall that the smoothing risk relates to uncertainty about what the investor's optimal lifetime consumption profile should look like when making consumption and savings decisions at time t; whereas, the consumption risk channel affects the investor's ability to smooth consumption conditional on having a particular preference for consumption smoothing. When consumption growth is more persistent, this increases the investor's ability to plan for future periods relative to, say iid consumption. All else equal, an investor with a stronger preference for smoothing consumption should prefer these states of the world. Note that the transition matrix (1.2) generated by the model calibration is given by

$$\Pi_{t,t+1} = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \begin{array}{c} \begin{array}{ccccc} s_1 & s_2 & s_3 & s_4 & s_5 \end{array} \\ \begin{pmatrix} 0.735 & 0.220 & 0.012 & 0.032 & 0.002 \\ 0.265 & 0.611 & 0.032 & 0.087 & 0.005 \\ 0.265 & 0 & 0.643 & 0 & 0.092 \\ 0.265 & 0 & 0 & 0.698 & 0.037 \\ 0.265 & 0 & 0 & 0 & 0.735 \end{pmatrix} \end{array}. \tag{1.10}$$

From time t perspective, s_2 and s_4 have a probability of 73.5% of remaining in a low consumption growth state, implying identical consumption persistence if the economy stays in these relative states. However, in spite of the fact that these states are identical aside from ψ_t and have identical consumption persistence over low consumption growth states, the model implies from Matrix (1.9) that s_2 is a state of high marginal utility while s_4 is a state of low marginal utility. The only way this can happen is if investors are better off in utility terms when persistence in consumption growth is high when $\psi_t = \psi_{\text{depr}}$ relative to states where $\psi_t = \psi_0$. If this is the case, then we would expect discount factors for s_2 and s_4 to diverge as consumption persistence increases. We can test this directly by solving the model for a grid of ρ_C and reporting the discount factors for s_2 and s_4 if the economy is in state s_2 at time t (the second row of Matrix (1.9)). These results are shown in Figure 1 and we see that indeed, the discount factors diverge as consumption persistence increases. The intuition of this result is that if consumption is persistent and investors have a stronger preference for consumption smoothing, they will be better able to plan for future periods in a way that will give them higher overall utility relative to states where they have a weak preference for smoothing.

Given that states $s_4 = (g_\ell, \gamma_0, \psi_{\text{depr}})$ and $s_5 = (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}})$ are low marginal utility states with low consumption growth, it may seem odd that these discount factors are always lower than when $s_1 = (g_h, \gamma_0, \psi_0)$ for low marginal utility states since consumption growth is high in this state. The only way for this to be true is if marginal utility is more sensitive to the smoothing risk than consumption risk. Or equivalently, the proportion of equilibrium asset prices explained by the smoothing risk investors face is larger than that of consumption risk. To determine if this is true, we solve for the equilibrium discount factors for s_4 and s_5 if the economy is in state s_1 at time t (the first row of Matrix (1.9)) for values of consumption growth volatility, the EIS offset parameter k_ψ and the risk aversion scale factor k_γ holding the other parameters fixed under the baseline calibration in each case. Varying the size of the parameters k_ψ and k_γ will lead to larger fluctuations in risk aversion and EIS in the model. We also normalize all discount factors by the discount factor in s_1 for ease of comparison. The results of this exercise are shown in Figure 2. It is clear from the figure, comparing across panels, that discount factors, hence marginal utility and asset prices, are much more sensitive to fluctuations in the EIS parameter than shocks to consumption growth or fluctuations in risk aversion. This latter point is consistent with our previous discussion that risk aversion will just scale up the effect of EIS fluctuations in states where both shift to irregular levels. This can be seen in Panels (c) as risk aversion magnitudes increase, for a fixed value of the EIS offset parameter, discount factors are shifted up and the line for s_5 lies strictly above the line for s_4.

Given the discussion so far, it is clear where the smoothing risk enters discount factors. The EIS measures how averse an investor is at time t to consumption variations *across future time periods along a deterministic path of consumption growth.* In our model, there is some uncertainty about the "right amount" of consumption variation given that an investor's preference for smoothing might increase with some small probability d as their EIS falls in some future period. As argued above, from the perspective of time t, states where this event is realized are not "bad" states per-se because this increased desire to smooth consumption is complemented by persistence in consumption growth. However, once the investor is in this state of an increased desire to smooth consumption, uncertainty about their ability to plan for the future will be seen as a risk. This is why investors are willing to pay a premium for the s_1 state contingent claim conditional on being in one of the rare states s_4 or s_5, to insure themselves against this smoothing risk.

1.4.2 Aggregate Asset Price Moments

In Table 2, under our baseline calibration, we report the model implied first and second moments and autocorrelations for equity returns, the risk-free rate, the equity premium, price-dividend ratios, and the dividend yield as well as the Sharpe Ratio. Because we are able to solve the model exactly, we do not rely on simulation or estimation to produce moments from the model. This means the model moments reported in Table 2 and elsewhere are population moments and are computed without sampling error. Also, since we do not assume lognormal returns, all the returns, prices, and dividends reported in Table 2 are exact (not transformed on a log basis) and our model can produce both price-dividends and the dividend yield. Along with the population moments implied by the model, we report the corresponding estimates for these moments from annual data over the sample period 1930-2013. As shown in Table 2, the model produces values for all reported moments within the 95% confidence interval (and in many cases within one standard error) of the data estimates with the exceptions of the price-dividend and dividend yield volatilities and the first order autocorrelations of price-dividends. In particular, the model does a good job matching the equity premium and Sharpe Ratio while simultaneously producing both a low expected risk free rate and high enough volatility of the risk free rate to match the data. This feature is something that is typically difficult to generate in the class of representative agent asset pricing models without assuming unreasonable levels of risk aversion. To further understand how the model is generating these features, we can look at the model implied equity and risk-free returns as well as expected returns to equity.

$$\begin{array}{cc} & R_f \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \begin{pmatrix} 1.0380 \\ 1.0235 \\ 1.0057 \\ 0.9419 \\ 0.9179 \end{pmatrix} \end{array} \quad \begin{array}{cc} & \mathbf{E}_t[R_m] \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \begin{pmatrix} 1.0828 \\ 1.0904 \\ 1.4763 \\ 0.9451 \\ 0.9335 \end{pmatrix} \end{array} \quad \begin{array}{cc} & \mathbf{E}_t[R_m - R_f] \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \begin{pmatrix} 1.0448 \\ 1.0669 \\ 1.4706 \\ 1.0032 \\ 1.0156 \end{pmatrix} \end{array} \quad \begin{array}{cc} & \pi \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \begin{pmatrix} 0.50 \\ 0.28 \\ 0.04 \\ 0.13 \\ 0.04 \end{pmatrix} \end{array}$$

The first thing to notice is that relative to periods of high consumption growth (s_1) if the economy is in a recession (s_2) then demand for the risk-free asset increases as agents rebalance their portfolios toward less risky securities. This pushes the price of the risk-free asset up and its net return down, as we see comparing s_1 and s_2 in the R_f vector. As expected, the inverse relationship shows up in expected equity returns as this rebalancing has the opposite effect on equity prices. If an exogenous shock elevates risk aversion (s_3) then these effects are only magnified because higher risk aversion induces even more portfolio rebalancing toward less risky securities driving the net return of the risk-free asset further down and expected equity returns even higher.

However, if there is an exogenous shock that depresses the EIS (s_4 and s_5) so that investors have a stronger preference for smoothing consumption returns for *both* the risk free rate and expected equity returns fall. The reason is that all assets in the economy are vehicles for transferring consumption across future periods, even risky ones. Therefore, even though consumption growth is low, the investors prefer even smoother consumption and are willing to buy assets that will achieve this goal. Investor demand pushes prices of both the risk-free rate and equities higher and their preference for smoothing in these periods is so strong that they are willing to accept negative returns to ensure a smooth consumption profile over future periods. Hence, investors end up paying a premium in the form of lower returns to transfer consumption into these rare states of depressed EIS.

As argued above, elevated risk aversion only amplifies the effect of a depressed EIS on discount factors so that if risk aversion is also elevated, demand for the risk-free asset is even higher, pushing its price up and return down. This can be seen comparing the gross risk-free return of 0.9419 in s_4 (a net loss of about 5%) with the smaller gross return of 0.9179 in s_5 (a net loss of about 8%). However, this accelerated increase in the price of the risk-free asset would make the price of the risky asset that pays off in state s_5 relatively more attractive than the one that pays off in state s_4. Therefore, equity prices go up slightly in s_5 relative to s_4 taking pressure off the risk-free rate, which is consistent with the expected equity returns being *lower* in state s_5 than in state s_4.

The dynamics just described generate volatility across states in the risk-free rate and expected returns and therefore, in the equity premium. As expected, in s_3 investors demand a very high risk premium to hold equities because low demand for risky assets in periods of elevated risk aversion drives prices down and investors must be compensated for this risk in the form of higher returns. In states with depressed EIS, we see that investors demand less of a risk premium than in the other three states even though the economy is in a recession due to a stronger preference for consumption smoothing, which increases demand for both risk-free and risky assets. Overall, these effects generate variation in the equity premium but with reasonable average levels for risk aversion because these states of irregular preferences happen very rarely in the model. The steady state probabilities in the π vector show that the model spends almost 80% of the time in states where investors have regular preferences. We only require rare and temporary periods of irregular preferences to generate the model's equity premium of 6.21.

Price Dividend Volatility

Although the model does a good job in matching the first moments of price-dividend ratios and dividend yields, the most obvious area where the model struggles is in generating enough volatility in these variables. Counterfactually low price-dividend volatility is an issue that the long-run risks models of Bansal and Yaron (2004) and Bansal et al. (2012) also struggle with, so despite this weakness our model is in good company. Those models also use recursive preference specifications but very different consumption and dividend dynamics than our model assumes.

There are a few things we might do to improve the model's ability to generate price-dividend volatility. First, our model has a very small state space and expanding the state space for consumption and dividend growth could potentially add additional variation that the current model is unable to capture. Second, the dividend growth process we have specified (leveraged consumption growth) is too auto-correlated and too strongly cross correlated with consumption growth (it is equal to 1 by construction) relative to dividends data. This strong correlation between dividend growth and consumption growth results in the model producing an unconditional contemporaneous correlation of 0.46 between excess returns and consumption growth, which is much too high relative to the low correlation found in the data. However, even though we do not assume separate processes for consumption and dividends, our model implied value of 0.46 is less than the value of 1.0 produced by the standard time-separable model and close to the value of 0.47 produced by Campbell and Cochrane (1999) from simulations at an annual frequency.[23] The reason this correlation is not 1.0 in our model is that some of the variation in returns is being explained by variation in preference parameters that are not directly tied to changes in consumption growth (transitioning between states 2-5 in the model). This counterfactual result, as Cochrane and Hansen (1992) point out, is a major factor in the empirical failures of the consumption-based

[23]The models of Barberis et al. (2001) and Bansal and Yaron (2004) produce a contemporaneous correlation between consumption growth and returns of 0.15, which is much closer to estimates from the data.

asset pricing model. Relaxing this unrealistic restriction in future iterations of the model would introduce more dividend volatility into the model and could improve the model's fit.

Alternative Calibrations

Given the model's ability to match key asset pricing moments, it is useful to look at a few alternative calibrations to reveal what features of the model are responsible for this success. In Table 1 we presented several different alternative calibrations to our baseline calibration. One point of debate between proponents of either long-run risk models following Bansal and Yaron (2004) or habits models following Campbell and Cochrane (1999) is whether or not consumption growth is independently and identically distributed (iid). The long-run risks model assumes a predictable, long run component in consumption growth, while the habits model assumes consumption is a random walk ($\rho_C = 0$). In our baseline calibration, we do not assume consumption is a random walk, we calibrate ρ_C to the data sample we have. However, in Table 1 we specify an alternative calibration (4) of the model with $\rho_C = 0$ that is otherwise nearly identical to our baseline calibration with the exception that regular level of risk aversion is calibrated to be 7.5 and the risk aversion scaling parameter $k_{elev} = 4.93$. We report the model fit in Table 3. As shown in the table, the model performs just as well under the assumption of iid consumption growth with the exception that the volatility of the risk-free rate is too high. The takeaway from this exercise is that the particular nature of the consumption growth dynamics being assumed as either iid or having a predictable component is not crucial for our model to fit the data.

Calibrations (1)-(3) in Table 1 are special cases of the baseline calibration that maintain the exact same calibration as the baseline but shut down variation in the EIS parameter, risk aversion or both. Calibration (1) sets $b = 0$, which shuts down time-variation in the risk aversion parameter and only allows the EIS parameter to be time-varying in order to highlight the importance of variation in the EIS. Comparing this calibration to the baseline, two features stand out. The first is that the EIS seems to be entirely responsible for the model's ability to match the moments for the risk free rate. Furthermore, since $\gamma_0 = 7.25$ in the baseline, this implies variation in the EIS is important for resolving the risk-free rate puzzle. Second, variation in the EIS also seems important for the model to produce high mean price-dividend ratios and what little variation in price-dividend ratios the model is able to generate.

Turning to calibration (2), which shuts down time-variation in the EIS and only allows risk aversion to be time-varying, we see that risk aversion is important for matching the moments for equity returns and the equity premium; however, it does so at the expense of the risk-free rate puzzle creeping in with almost no volatility and a much higher mean for the risk-free rate. The last baseline special calibration (3) is the case where both parameters are constant over time so that the Markov transition matrix is equivalent to the one in Mehra and Prescott (1985). As expected, this calibration is unable to generate a large equity premium and is also prone to the risk-free rate puzzle with $\gamma_0 = 7.25$.

Alternative calibrations (1b) and (2b) are different from the baseline calibration and attempt a "best fit" for the case when $b = 0$ and $d = 0$. The purpose of these calibrations are to answer the hypothetical question "if we had to choose just one parameter to be time-varying, which one would we prefer?" Looking at calibration (1b), which only allows the EIS parameter to be time-varying is similar to the baseline with two exceptions. First, the dividend leverage parameter is higher at 5.83, however, at this value the model produces the exact value of the sample estimate of dividend volatility (12.53) as seen in Table 3. In other words, this is the value of the dividend leverage parameter that would be estimated from Equation (1.1) using the sample moments of μ_D and σ_D. The second difference is that the constant risk aversion parameter is set at 9.5, which is still below the benchmark of 10. It is clear from the table that this calibration does as good or better in some cases than our baseline calibration.

Alternative calibration (2b) sets $d = 0$, which only allows risk aversion to vary over time. The main difference between this calibration and our baseline is that k_γ is now 4.75, implying the model requires a higher level of irregular risk aversion (28.5) although the mean risk aversion of 7.86 is still reasonable. Under this calibration the model does reasonably well, although it does not generate enough risk-free rate volatility and does not perform as well as the baseline or alternative calibrations (1b). The overall takeaway from the model performance under these alternative calibrations is that, although both are important, allowing the EIS to be time-varying seems to be more crucial in the model fitting these asset pricing moments than time-varying risk aversion since calibration (1b) does better than (2b). Time variation in the EIS parameter seems particularly important for simultaneously generating both a low expected risk free rate and high enough volatility of the risk free rate, matching the equity premium and Sharpe Ratio, and maintaining a risk aversion coefficient of less than 10.

1.4.3 Predictability

A large empirical literature has formed documenting the ability of price-dividends to predict excess stock returns and their inability to predict future dividend growth (Fama and French (1988), Campbell and Shiller (1988) and Hodrick (1992) among others). This feature of aggregate asset prices has become standard for evaluating the performance of asset pricing models. In Table 4 we report the predictability results implied by our model under the baseline calibration along with estimates from the data for both the price-dividend regressor coefficient and R-squared. However, before discussing these results, a word of caution regarding the validity of these estimations is in order. As Stambaugh (1999) points out, because the price-dividend ratio time-series is highly persistent with innovations correlated with the innovations in excess returns, the coefficient estimates from these predictive regressions will be biased. Furthermore, the results in Cavanagh, Elliot, and Stock (1995) imply this bias is present as well in the t statistics and R-squared estimates. Therefore, as Beeler and Campbell (2012) discuss, the predictability of excess returns can only be used to reject a model statistically at horizons longer than one year in the annual data while the bias is much less of a concern for consumption and dividend growth predictability.

With this in mind, the top panel in Table 4 shows that our model does quite well at producing the predictability of excess returns by price-dividend ratios at long horizons. In particular, the model implied R-squared statistics are within one standard deviation of their data estimates. Moreover, as in the data, the model implied coefficients are decreasing while predictability is increasing with the horizon.[24] Our model also produces virtually no predictability of consumption growth or dividend growth at all horizons with coefficient estimates similar to those estimated from the data. Beeler and Campbell (2012) are critical of the long run risks model for not generating enough excess return predictability and generating too much consumption and dividend growth predictability and the model output in Table 4 indicates that our model is not subject to these critiques.[25] Likewise Bansal et al. (2012) point out a shortcoming of the Campbell and Cochrane (1999) habits framework is that it counterfactually implies too much predictability of price-dividend ratios from *past* consumption growth. The final panel in Table 4 shows that our model produces very little predictability of price-dividend ratios by past consumption growth, which is consistent with the data.[26]

[24] Bansal et al. (2012) suggest using dividend yields adjusted by subtracting the real risk-free rate to reduce the persistence in the return predictability regressor to help counteract the bias pointed out by Stambaugh (1999). They report that this adjustment leads to return predictability in the data that is weaker than when using the price dividend ratio, with five-year horizon R-squared droping from 31% to %14. We do not report our model's results under this alternative specification, however, it appears that less predictability would only serve to help our model match predictability in the data.

[25] Beeler and Campbell (2012) also conduct their analysis using the Bansal et al. (2012) calibration and report the model does better at consumption and dividend predictability but need extreme movements in volatility to produce results roughly in line with the data.

[26] The trend in the coefficient estimates is the opposite of what is estimated from the data. However, these point estimates are clearly estimated with a lot of noise (very wide confidence intervals) and are not statistically different from zero anyway.

Our model is able to simultaneously match both forward and lagged consumption predictability features in the data because innovations in the stochastic discount factor are driven by innovations in preferences and these parameters are only moderately correlated with consumption growth as reported in Table 1. This results in a model implied contemporaneous correlation between price-dividend ratios and consumption growth of 0.0645, compared with an estimate of 0.0643 (se 0.1196) in annual data over the 1930-2013 sample period. This result is rather surprising given the fact that we assume, through our simplifying assumptions about the dividend growth process, that consumption and dividends are perfectly correlated. This result suggests the smoothing risk associated with fluctuations in the EIS parameter is driving fluctuations in equity prices more than consumption growth risk. That fluctuations in the EIS dominate fluctuations in consumption volatility in terms of their effect on equilibrium discount factors, and hence their effect on marginal utilities and equilibrium prices, speaks to this fact.[27] The takeaway from these predictability results is that our model is able to produce excess return predictability at long horizons consistent with what we see in the data while simultaneously producing no predictability of consumption or dividend growth and no predictability of price-dividend ratios by lagged consumption, something (as far as we are aware) that the current asset pricing literature is unable to do.

Alternative Calibrations

It is useful to look at the alternative calibrations of our model to see if we can identify what is driving the predictability results. Table 5 reports the model implied predictability results under the three baseline special cases as well as the best fit calibrations. Comparing excess return predictability across calibrations, the model can still produce reasonable predictability of excess returns under iid consumption growth, implying again that our particular

[27]This was shown previously in Figure 2.

assumption of non-iid consumption growth is not what is driving our results. However it is obvious from comparing calibrations (2) and (2b) to the other baseline special cases and best fit calibration (1b) that excess return predictability is driven almost entirely by time-varying risk aversion and that time-varying EIS has little or nothing to do with this result. However, it is also clear from comparing calibrations (1) and (1b) to the other baseline special cases and best fit calibration (2b) that time-variation in the EIS parameter is what is driving the model's ability to produce low consumption and dividend growth predictability, as discussed in the previous section. Likewise, looking at the model implied predictability of price-dividend ratios by lagged consumption growth it is clear from comparing calibrations (1) and (1b) to the others that time-varying EIS is much more crucial in generating this low predictability than time-varying risk aversion.

1.4.4 Countercyclical Variation of the Risk Premium

It is a well known empirical fact that risk premia vary over time and this variation in equity risk premium leads to volatile asset prices and excess return predictability.[28] We report several features of the equity risk premium implied by our model that are consistent with this fact in Table 6. Under the baseline calibration our model produces an equity risk premium that is quite volatile. In addition, the model produces risk premium volatility that is itself quite volatile. Looking at the alternative calibrations, it is clear that time-variation in risk aversion is crucial for generating this volatility, which is consistent with our earlier finding that time-variation in risk aversion is what is driving excess return predictability in the model. This is also consistent with Campbell and Cochrane (1999) that attribute time-variation in the equity risk premium to countercyclical risk aversion.

Furthermore, Chou, Engle, and Kane (1992) show that, for U.S. data, the equity premium and the Sharpe Ratio are both counter-cyclical. Although we do not replicate their

[28] For example see Fama (1984), Harvey (1989), Fama and French (1989) and Li (2001).

estimates here, we show in Table 6 under the baseline calibration, our model is able to qualitatively match the data by generating both a counter-cyclical risk premium and Sharpe Ratio. Again, looking at the alternative calibration (4), the results still hold under iid consumption so this results is not being driven by our assumptions about consumption growth. Comparing across baseline special case calibrations (1)-(3) as well as the best fit calibrations (1b) and (2b), the main takeaway from Table 6 is that time variation in the EIS parameter is crucial for the model to produce counter-cyclicality of the Sharpe Ratio.

While this is an interesting result, more work needs to be done to understand why exactly the smoothing risk associated with fluctuations in the EIS is important for generating a counter-cyclical Sharpe Ratio in the model. Nevertheless, Guvenen (2009) states that "with few exceptions this counter-cyclicality of the market price of risk has been difficult to generate in consumption-based asset pricing models" and concludes that *heterogeneity* in the EIS is crucial to produce the stylized facts in 6.[29] That these exceptions include Campbell and Cochrane (1999), Bansal and Yaron (2004), Bansal et al. (2012) and Wachter (2013) speaks favorably to the fact that our model is also able to produce a counter-cyclical Sharpe Ratio.

1.4.5 Real Term Structure

Estimates for the real term structure are very limited due to the unavailability of long time series for inflation indexed bonds. Because of this, there is some debate on the empirical nature of the real term structure. Beeler and Campbell (2012) state that the observed term structure on U.S. Treasury inflation-protected securities (TIPS) has never had a quantitatively significant negative slope. Wachter (2013) claims that U.S. Treasury yield curves are upward sloping (on average) in the data. Piazzesi and Schneider (2006) also cite evidence that the average real yield curve constructed from the U.S. TIPS data is upward sloping. Other studies have shown evidence from real bonds in the U.K. of a downward sloping real

[29] Guvenen (2009) page 1735.

yield curve.[30] Although empirical estimates of the real yield curve should be taken with caution, our model is calibrated to match U.S. equity data. Therefore, we think the upward slope of the real yield curve in the U.S., as suggested by TIPS data, is the appropriate stylized fact for our model. Table 7 reports the real term structure generated by our model under the baseline calibration. The model is able to produce an upward sloping real yield curve with a yield spread of 15 basis points at a 10 year horizon. In addition to the slope, the real yields at long horizons produced by the model are never negative and are in the ballpark of 2%, which is roughly consistent with what Campbell, Shiller, and Viceira (2009) report for the real yield on long-term TIPS.

Backus, Gregory, and Zin (1989) point out that that under the standard CRRA utility model with values of the coefficient of relative risk aversion below ten, the average returns of long bonds in excess of the short rate are small and negative. This "bond premium puzzle" has traditionally been difficult for consumption-based asset pricing models to overcome. Our model is primarily focused on matching aggregate stock prices and we do not use any bond data in calibrating or solving the model. Given this, it is surprising that our model, with reasonable values for risk aversion, is able to overcome the bond premium puzzle and yield magnitudes that appear consistent with real bond data.[31] Along this dimension, our model compares favorably to several other asset pricing models. The habits framework of Campbell and Cochrane (1999), as demonstrated by Wachter (2006), is able to overcome the bond premium puzzle for real bonds. However, for instance, the long-run risk model of Bansal and Yaron (2004) and Bansal et al. (2012) are unable to produce these features of the real term structure while the rare disasters model of Wachter (2013) is also unable to produce an upward sloping real term structure.

[30] See Piazzesi and Schneider (2006) for a more detailed discussion.

[31] In the baseline calibration, the coefficient of relative risk aversion is 7.25 in the vast majority of periods, while the average level of risk aversion is 8.6, both values less than the benchmark of ten.

Looking at calibrations (1) and (1b) in Table 7 compared with calibrations (2), (3) and (2b) it is clear that time-variation in the EIS is important in generating a steeply, upward sloping real yield curve. When $b = 0$, so that time-variation in risk aversion is shut down and only the EIS parameter is allowed to vary, the yield spread between the 10 year and 1 year bond is 28 basis points in the baseline special case and 95 basis points in the best fit case of $b = 0$. Also, note that calibration (4) with iid consumption produces a yield spread of 0.57, again indicating this feature of the model is not being driven by our assumption on consumption dynamics. These results suggest that smoothing risk is important for long-term bonds to be viewed as risky, which generates an upward sloping yield curve.

To investigate why smoothing risk is generating this result, it would be useful to look at the model implied risk premium for long-term bonds.[32] However, due to the non-linearity of the stochastic discount factor, we do not have a closed form solution for this risk premium. Instead, we report the risk premium on bonds for the standard Epstein and Zin (1989) model under log-normal consumption growth shocks and an EIS set to one, as derived in Piazzesi and Schneider (2006), to guide our discussion:

$$E_t\left(rx_{t+1}^{(n)}\right) = -cov_t\left(m_{t+1}, E_{t+1}\sum_{i=1}^{n-1} m_{t+1+i}\right) - \frac{1}{2}var_t\left(p_{t+1}^{(n-1)}\right) \tag{1.11}$$

where $rx_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)}$ is the return on buying an n-period real bond at time t for price $p_t^{(n)}$ and selling it at time $t+1$ for $p_{t+1}^{(n-1)}$ in excess of the short rate. The covariance term in Equation (1.11) is the risk premium on long-term bonds while the variance term comes from Jensen's inequality. From Equation (1.11), it is clear that the risk premium on bonds is due to the covariance between marginal utility m_{t+1} and the price of the long-bond. As Piazzesi and Schneider (2006) point out, the yield curve is upward sloping (on average) if the right hand side of Equation (1.11) is positive on average. Therefore, Equation (1.11)

[32] We refer to the risk premium for bonds as defined in Piazzesi and Schneider (2006): the return on buying an $n-$period real bond at time t for price $p_t^{(n)}$ and selling it at time $t+1$ for $p_{t+1}^{(n-1)}$ in excess of the short rate.

implies that the yield curve is upward sloping when marginal utility and bond prices are negatively correlated.

First, consider what happens if we shut down time variation in both the EIS and risk aversion. Then expected changes in marginal utilities are only driven by consumption growth shocks. Piazzesi and Schneider (2006) show that under Epstein and Zin (1989) preferences the risk premium on bonds implied by our model in this case should be negative, which it is as shown in calibration (3) of Table 7. Recall that marginal utilities in our model are driven by shocks to risk aversion and the EIS in addition to consumption growth shock and are given by Equation (1.6). Ignoring the Jensen's Inequality term (since bond prices are not very volatile) we can re-write the bond risk premium as

$$E_t\left(rx_{t+1}^{(n)}\right) = -cov_t\left((m_{t+1}^{ez}(\gamma_t,\psi_t) + sr_{t+1}), E_{t+1}\sum_{i=1}^{n-1}(m_{t+1+i}^{ez}(\gamma_{t+i},\psi_{t+i}) + sr_{t+1+i})\right) \tag{1.12}$$

where as before, the second term in the covariance expression of Equation (1.12) is the price of a long-term bond. Of course, the model's true risk premium on long-bonds will be a more complicated function that will depend on covariances between all the random variables in the model, so this expression is meant only to be roughly illustrative. Consider allowing only the risk aversion to be time varying so that $sr_{t+1} = 0$ in Equation (1.12). From the perspective of time t, marginal utility is high in every state that risk aversion is elevated (Section 1.4.1). Also, increased risk aversion should push prices for bonds up relative to risky assets that pay off in those future states. Therefore the correlation between marginal utilities and bond prices is positive, which implies risk premium on long-term bonds are negative from Equation (1.12). This is indeed the case looking at the real yield curve for calibrations (2) and (2b) in Table 7.

Now consider allowing the EIS to be time varying so that $sr_{t+1} \neq 0$ for all t. From the perspective of time t, marginal utility is low in every state that the EIS is depressed (Section 1.4.1). Also, we argued that when the EIS is depressed, investors have a stronger preference for consumption smoothing and they will demand more of any asset that transfers consumption across periods (Section 1.4.2). Therefore, the price of long-term bonds will be pushed up as investors demand more of these bonds. Hence, marginal utility is negatively correlated with bond prices, which generates a positive risk premium on bonds. This is apparent looking at the real yield curve for calibrations (1) and (1b) in Table 7.

Allowing for both risk aversion and the EIS to be time-varying in our baseline calibration also produces a positive risk premium on long-bonds. This is true even though shocks to consumption growth and risk aversion fluctuations push the risk premium in the opposite direction (negative) as fluctuations in the EIS (positive). The reason is that, as previously shown in Figure 2, marginal utilities are more sensitive to fluctuations in the EIS than consumption volatility or risk aversion fluctuations so the former effect on the risk premium on long-term bonds dominates. Therefore, the consumption and risk aversion hedging of long-term bonds is dominated by the positive risk premium being generated by the smoothing risk.

This analysis supports the implication of the model that smoothing risk generates an upward sloping real yield curve. Intuitively, the reason that long-term bonds are viewed as risky by the investor is because these bonds give investors a stream of consumption in future periods $t+i+1$ (for $i = 1, 2, \dots$) that is consistent with their preference for smoothing at time t. However, if their preference for smooth consumption changes before these bonds pay off, they are stuck holding assets that give them a different consumption profile than what their new preferences would optimally choose. Hence, the uncertainty coming from the smoothing risk affects an investor's ability to plan over long horizons. However, agents in the model are rational and there is no dynamic inconsistency because this uncertainty is priced into assets in equilibrium as a positive risk premium for long-term bonds.

1.5 Discussion

The model results in the previous section provide compelling evidence that time-variation in the EIS parameter seems to be the primary channel allowing the model to match aggregate asset pricing moments, consumption and dividends predictability, counter-cyclicality of the market price of risk, and the real term structure. Time-varying risk aversion helps the model fit better but is itself the primary channel through which the model is able match the empirical evidence that price-dividend ratios predict excess stock returns at long horizons and generate a volatile equity premium. Furthermore, we have argued that these fluctuations in the EIS parameter effects equilibrium asset prices in the model through the smoothing risk channel. However, the model remains agnostic as to why investor preferences fluctuate in such a way as to introduce this additional risk being priced into assets.

In the discussion that follows, we provide arguments for these mechanisms under the behavioral interpretation in Section 1.2.9 that rare exogenous shocks coinciding with recessions induce fear in the market that shifts investor preferences to irregular levels. Given that market fundamentals, which are captured by realized consumption growth, are the same across regular and irregular preference states, we can think of these fluctuations in preferences as overreactions to bad news. Hence, investors make decisions based on fear induced irregular preferences resulting in optimal consumption and savings choices that depart from what these investors otherwise would have made given the same news about the fundamental state of the economy. Under this interpretation, fear influences investor preferences through two channels: investors' contemporaneous appetite for risk and their desire to smooth consumption across future states of the economy. We emphasize that this behavioral interpretation is not necessary for the model results to hold, it merely guided our assumptions restricting the transition matrix and provides an intuitive explanation for how assets are priced in this model economy; this interpretation is also consistent with the evidence presented by Guiso et al. (2013) and Cohn et al. (2013) that fear influences investor choice in ways not attributable to standard risk factors.

1.5.1 Excess Safety Motive

When an investor's appetite for risk is elevated due to fear *but their preference for consumption smoothing is unchanged at its regular level*, we have seen that discount factors behave as expected in a standard consumption-based asset pricing model. However, looking at Matrix (1.9), investors pay premiums $(2.63, 2.15)$ for contingent claims paying off in recessions when marginal utility is high under fear-induced elevated risk aversion that are *larger* than premiums $(1.38, 1.13)$ for claims in recessions when there is no fear in the market. Likewise, investors require a larger discount for state contingent claims in periods of fear than they otherwise would for claims paying in expansions when marginal utility is low (0.03 versus 0.68). This appetite for risk results in investors paying too much for the risk-free asset, in the form of accepting lower returns, as they rebalance their portfolios away from risky assets. The key thing to note is that the value of realized consumption growth is the same ($G_t = g_\ell$) in states s_2 and s_3, hence relative to the market fundamentals investors are overly conservative in taking risks when in irregular periods of elevated risk aversion. So we can think of investors as having an "excess safety" motive, induced by fear, for investments relative to what the market fundamentals would otherwise dictate.

1.5.2 Excess Frugality Motive

Risk aversion only measures how averse an investor is at time t to variation in consumption *across different states* at time $t+1$. However, the EIS measures how averse an investor is at time t to consumption variation *across future time periods* along a determinist path of consumption. Therefore, when investors are fearful regarding the future states of the economy they might prefer consumption profiles that are smoother because they are worried about not having enough to eat tomorrow and over longer horizons. In this case, fear induces a stronger preference for smoothing consumption than what the fundamentals of the economy dictate because the persistence of consumption growth is unchanged across fear and regular states. The limiting case of this strong preference for smoothing would be that investors guarantee for sure that they have the same amount of consumption in every period, even if market fundamentals indicate a different consumption and savings decision under regular preferences for smoothing. Hence, as mentioned previously, one way to think of the effect of fear on investor preferences is that fear induces a preference for consumption rationing that is unrelated to market fundamentals. This will tend to drive prices up on *any* asset that allows the investor to smooth consumption and their fear induced preference for smoothing is so strong that they are willing to accept negative returns in these fear states. In this sense investors have an "excess frugality" motive in fear states because they will pay more than they should in the form of lower (negative) returns given the fundamentals of the economy.

This discussion points to the following conclusions. When rare shocks occur that induce fear in the markets and cause investors to have temporary, elevated risk aversion, this shock induces an excess safety motive: investors pay a lot for the risk-free asset—more than the fundamentals say they should—and subsequently demand a large risk premium to hold risky assets. However, if this fear shock causes a decreased EIS and a stronger preference for consumption smoothing, the shock induces an excess frugality motive: investors are willing to pay a lot—more than the fundamentals say they should—for all assets that transfer consumption to future periods. The low risk premiums in these states offset the very high risk premiums in the excess safety state and result in a model implied equity premium consistent with the data. Overall, these fluctuations generate the variation in asset prices that are crucial for the model to match many of the stylized facts of aggregate U.S. asset prices.

1.6 Conclusion

Much of the current literature on consumption based asset pricing attempts to explain fluctuations in aggregate asset prices through shocks to the aggregate consumption process, which is accomplished by specifying increasingly complex dynamics for consumption. Many studies have considered alternative preference specifications to the standard CRRA preferences. An influential subset of these studies has indicated that time variation in risk aversion is important for matching various stylized facts of U.S. asset prices. In addition, a few studies have suggested that accounting for time variation in the EIS is also potentially important for explaining asset prices. We develop a model with recursive preferences along the lines of Epstein and Zin (1989) that relaxes both assumptions of constant risk aversion and constant EIS parameters without departing from the simple consumption dynamics of Mehra and Prescott (1985).

Our parsimonious model with a limited state space nests the model of Mehra and Prescott (1985). We show that rare and temporary periods of irregular levels of the EIS and risk aversion can quantitatively explain numerous regularities in U.S. asset prices: the equity premium and risk-free rate puzzles, excess return and consumption growth predictability, a countercyclical risk premium, and an upward-sloping real yield curve. The ability of our model to simultaneously generate excess return predictability and no predictability in consumption growth (or lagged consumption growth predicting price-dividend ratios) along with a countercyclical risk premium and an upward sloping real yield curve is something that models in the extensive consumption-based asset pricing literature appear to be unable to do. A novel implication of our model is that, although counter-cyclical risk aversion is key for producing excess return predictability and countercyclical risk premium, small pro-cyclical fluctuations in the EIS generate a new smoothing risk channel for asset prices; furthermore, this new risk channel is important for producing most of the other challenging asset pricing regularities. This smoothing risk reflects uncertainty in investors' *ability to plan* for future consumption due to fluctuations in the EIS. Therefore, the model identifies a new risk channel that is distinct from the usual consumption risk governing investors' *ability to smooth* consumption absent such EIS fluctuations.

We also present a behavioral interpretation of sophisticated investors with rational expectations to explain our results: fear in the markets induces periods of excess safety or excess frugality where investors pay "too much" to smooth consumption or hedge against risk in the form of accepting lower returns relative to what market fundamentals dictate. Under this interpretation, our model provides a theoretical framework, consistent with investor behavior not reflected in traditional fundamental risk factors, to investigate the idea that psychological factors, such as fear, might alter investor preferences and drive fluctuations in aggregate asset prices.

Overall, our results suggest there is value in pursuing future research that relaxes the assumption that preference parameters are constant over time, particularly the EIS parameter, which has been largely neglected in the literature. Furthermore, our results motivate future empirical work to estimate and provide further evidence regarding time-varying risk aversion and the EIS. Exploring this channel as a source of model misspecification could lead to fruitful advances in our understanding of what is driving asset prices and risk premiums.

Table 1

Model Calibration

This table provides the baseline and alternative calibrations for the model at an annual frequency. The moments for consumption and dividends are calibrated to the 1930-2013 sample period. Conditional on transitioning to a state with low consumption growth, elevated risk aversion, $\gamma_{\text{elev}} = k_\gamma \gamma_0$, occurs with probability b, and depressed EIS, $\psi_{\text{depr}} = \psi_0 - k_\psi$, occurs independently with probability d. Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down.

			Baseline Special Cases				Best Fit	
			(1)	(2)	(3)	(4)	(1b)	(2b)
		Baseline	$b = 0$	$d = 0$	$b = 0$, $d = 0$	$\rho_C = 0$	$b = 0$	$d = 0$
Time Varying Risk Aversion		Y	N	Y	N	Y	N	Y
Time Varying EIS		Y	Y	N	N	Y	Y	N
Parameter	Symbol							
Mean Consumption Growth	μ_C	1.89	1.89	1.89	1.89	1.89	1.89	1.89
Consumption Growth Volatility	σ_C	2.15	2.15	2.15	2.15	2.15	2.15	2.15
Consumption Growth Autocorr.	ρ_C	0.47	0.47	0.47	0.47	0	0.47	0.47
Mean Dividend Growth	μ_D	1.97	1.97	1.97	1.97	1.97	1.97	1.97
Dividend Leverage Factor	ϕ_D	4.5	4.5	4.5	4.5	4.5	5.83	4.25
Time Discount Factor	δ	0.993	0.993	0.993	0.993	0.993	0.993	0.999
Risk Aversion, Regular	γ_0	7.25	7.25	7.25	7.25	7.50	9.5	6
Elevated Risk Aversion Factor	k_γ	3.24	—	3.24	—	4.93	—	4.75
Low Growth Cond. Probability	b	0.05	0	0.05	0	0.05	0	0.05
EIS Parameter, Regular	ψ_0	0.956	0.956	0.956	0.956	0.968	0.956	0.965
Depressed EIS Offset	k_ψ	0.002	0.002	—	—	0.002	0.003	—
Low Growth Cond. Probability	d	0.125	0.125	0	0	0.125	0.100	0
$\mathbf{E}[\gamma_t]$		8.60	7.25	8.60	7.25	8.90	9.5	7.86
$\mathbf{E}[\psi_t]$		0.9556	0.9556	0.956	0.956	0.9678	0.9556	0.965
$Corr(\gamma_t, G_t)$		-0.30	—	-0.30	—	-0.22	—	-0.30
$Corr(\psi_t, G_t)$		0.39	0.40	—	—	0.32	0.35	—

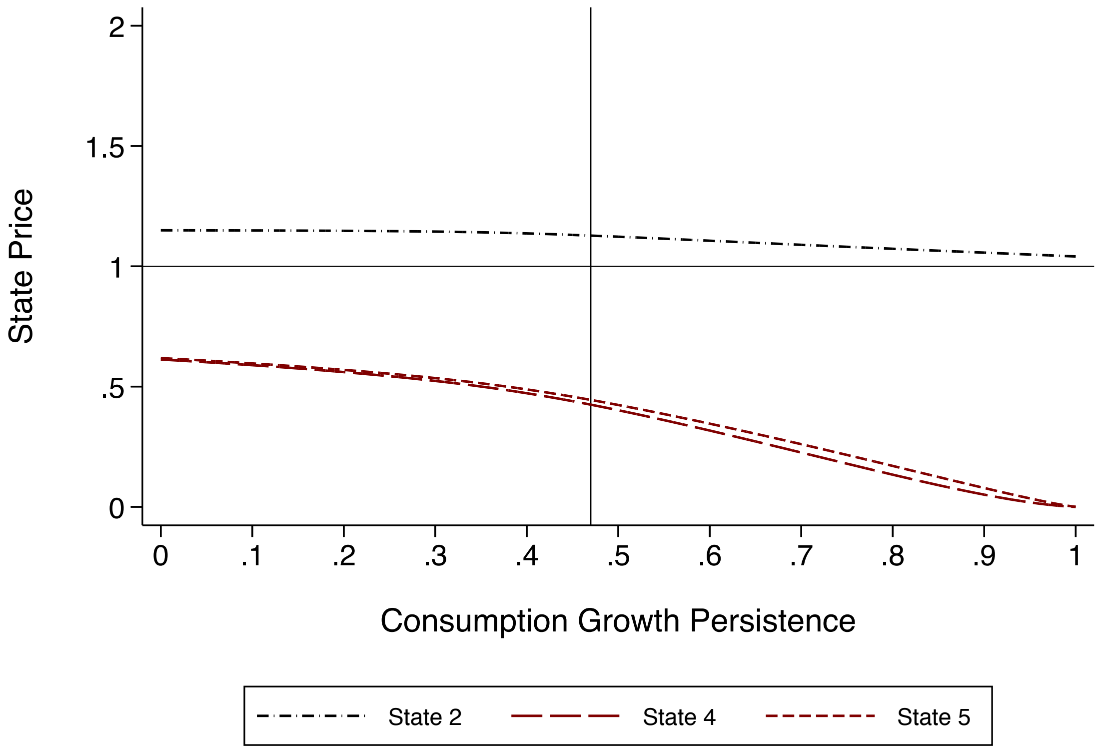

Figure 1

This figure plots the equilibrium discount factors from $s_t = \{s_2\}$ to $s_{t+1} \in \{s_2, s_4, s_5\}$ where $\{s_2, s_4, s_5\} = \{(g_h, \gamma_0, \psi_0), (g_\ell, \gamma_0, \psi_0), (g_\ell, \gamma_0, \psi_{\text{depr}}), (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}})\}$ for values for the persistence of consumption volatility. The vertical line indicates the value of $\rho_C = 0.47$ in the baseline calibration of the model. The figure illustrates that as persistence in consumption growth increases, discount factors in s_2 and s_4 diverge. This divergence in discount factors implies that investors are better off in utility terms when persistence in consumption growth is high when they have a strong preference for smoothing ψ_{depr} relative to states with a weaker preference for smoothing $\psi_t = \psi_0$.

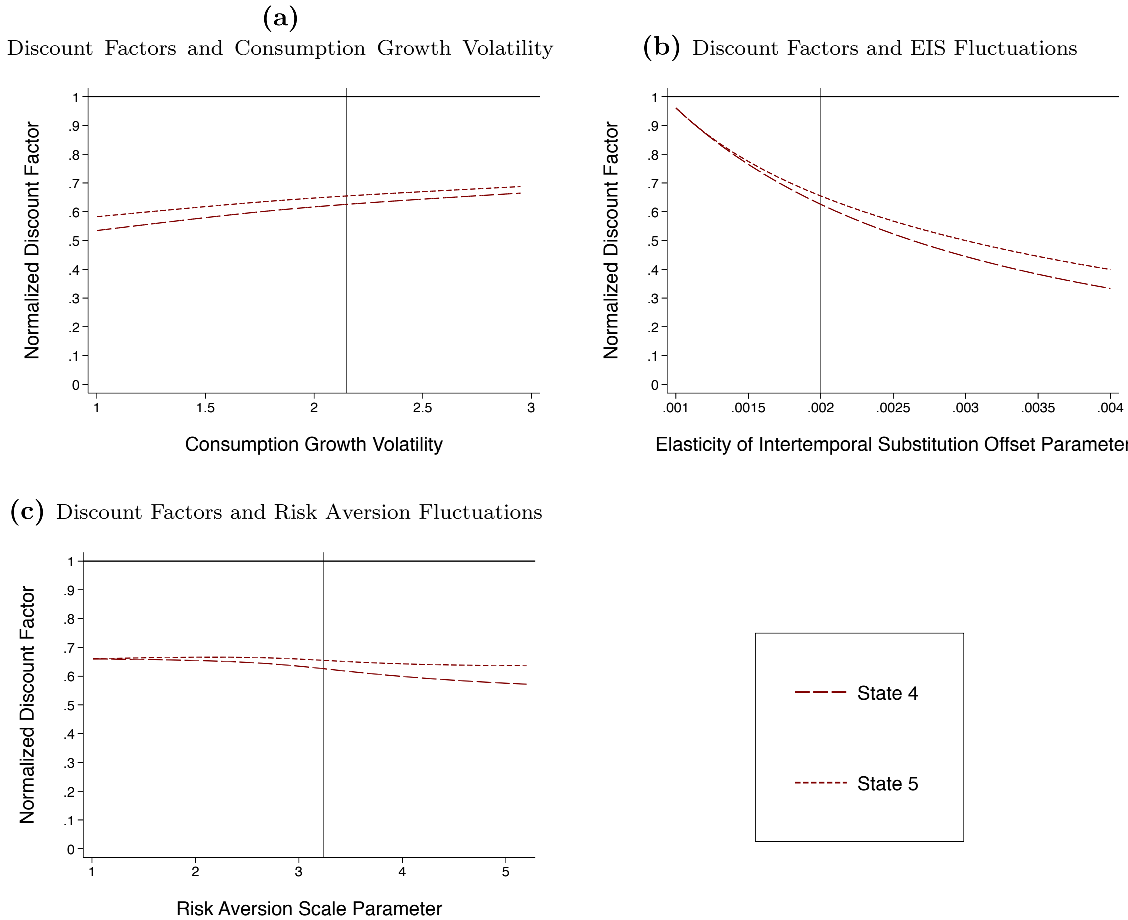

Figure 2

This figure plots the equilibrium discount factors from $s_t = \{s_1\}$ to $s_{t+1} \in \{s_1, s_4, s_5\}$ where $\{s_1, s_4, s_5\} = \{(g_h, \gamma_0, \psi_0), (g_\ell, \gamma_0, \psi_{\text{depr}}), (g_\ell, \gamma_{\text{elev}}, \psi_{\text{depr}})\}$. All of the discount factors reported in the figures are normalized by s_1, hence all discount factors are relative to the horizontal line at the value of 1. The vertical line in each panel indicates the value of that parameter in the baseline calibration of the model. Panel (a) solves the model and generates equilibrium discount factors for values of consumption volatility holding everything else fixed according to the baseline calibration. Panels (b) and (c) do the same thing over values for the EIS offset parameter k_ψ and the risk aversion scaling parameter k_γ. The vertical line in each graph indicates the parameter's value in the baseline calibration of the model. Comparing states s_4 and s_5 across the graphs, these figures illustrate clearly that equilibrium discount factors and hence, marginal utility and asset prices are much more sensitive to fluctuations in the EIS parameter than shocks to consumption growth or fluctuations in risk aversion.

Table 2

Asset Price Moments

This table provides the model implied asset pricing moments at an annual frequency for the baseline calibration in Table 1. The sample period is 1930-2013 and all data moments are estimated using 10 Newey West lags for heteroskedasticity and autocorrelation consistent standard errors. All returns, prices and dividends are exact and not transformed on a log basis.

Moment	Data	SE	95% CI	Model
$E(R_m)$	7.95	1.83	[4.35, 11.55]	7.68
$\sigma(R_m)$	19.50	1.78	[16.01, 22.98]	22.49
$AC1(R_m)$	-0.02	0.08	[-0.17, 0.13]	-0.08
$E(R_f)$	0.41	0.74	[-1.04, 1.87]	1.47
$\sigma(R_f)$	3.69	0.76	[2.20, 5.18]	3.73
$AC1(R_f)$	0.61	0.07	[0.48, 0.74]	0.67
$E(R_m - R_f)$	7.54	1.93	[3.75, 11.32]	6.21
$\sigma(R_m - R_f)$	19.52	2.29	[15.02, 24.01]	21.99
$AC1(R_m - R_f)$	0.01	0.09	[-0.15, 0.18]	-0.12
Sharpe Ratio	0.39	0.12	[0.15, 0.62]	0.28
$E(P/D)$	32.17	4.94	[22.48, 41.86]	25.06
$\sigma(P/D)$	16.12	3.67	[8.93, 23.32]	4.25
$AC1(P/D)$	0.91	0.06	[0.80, 1.00]	0.65
$E(D/P)$	3.82	0.46	[2.92, 4.72]	4.13
$\sigma(D/P)$	1.68	0.23	[1.24, 2.12]	0.91
$AC1(D/P)$	0.76	0.10	[0.57, 0.95]	0.63
σ_D	12.53	3.07	[6.52, 18.55]	9.68

Table 3

Asset Price Moments - Alternative Calibrations

This table provides the model implied asset pricing moments at an annual frequency for the baseline and alternative calibrations in Table 1. The sample period is 1930-2013 and all data moments are estimated using 10 Newey West lags for heteroskedasticity and autocorrelation consistent standard errors. Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down.

				Model						
					Baseline Special Cases				Best Fit	
					(1)	(2)	(3)	(4)	(1b)	(2b)
				Baseline	$b = 0$	$d = 0$	$b = 0$ $d = 0$	$\rho_C = 0$	$b = 0$	$d = 0$
Time Varying Risk Aversion				Y	N	Y	N	Y	N	Y
Time Varying EIS				Y	Y	N	N	Y	Y	N
Moment	Data	SE	95% CI							
$E(R_m)$	7.95	1.83	[4.35, 11.55]	7.68	4.51	8.54	5.53	6.93	6.47	8.21
$\sigma(R_m)$	19.50	1.78	[16.01, 22.98]	22.49	13.70	21.33	14.35	22.70	19.75	22.42
$AC1(R_m)$	-0.02	0.08	[-0.17, 0.13]	-0.08	0.05	-0.04	0.08	-0.20	0.00	-0.05
$E(R_f)$	0.41	0.74	[-1.04, 1.87]	1.47	1.78	2.16	2.25	1.13	0.71	1.57
$\sigma(R_f)$	3.69	0.76	[2.20, 5.18]	3.73	3.45	1.07	1.01	6.17	5.40	1.08
$AC1(R_f)$	0.61	0.07	[0.48, 0.74]	0.67	0.66	0.50	0.47	0.44	0.68	0.50
$E(R_m - R_f)$	7.54	1.93	[3.75, 11.32]	6.21	2.73	6.38	3.28	5.80	5.77	6.64
$\sigma(R_m - R_f)$	19.52	2.29	[15.02, 24.01]	21.99	12.93	21.41	14.30	21.86	18.54	22.56
$AC1(R_m - R_f)$	0.01	0.09	[-0.15, 0.18]	-0.12	-0.03	-0.07	0.01	-0.17	-0.05	-0.08
Sharpe Ratio	0.39	0.12	[0.15, 0.62]	0.28	0.21	0.30	0.23	0.27	0.31	0.29
$E(P/D)$	32.17	4.94	[22.48, 41.86]	25.06	48.76	20.12	33.44	30.81	29.88	22.45
$\sigma(P/D)$	16.12	3.67	[8.93, 23.32]	4.25	5.08	2.62	2.01	5.13	5.38	3.15
$AC1(P/D)$	0.91	0.06	[0.80, 1.00]	0.65	0.64	-0.07	0.47	0.45	0.67	0.63
$E(D/P)$	3.82	0.46	[2.92, 4.72]	4.13	2.07	5.08	3.00	3.34	3.44	4.58
$\sigma(D/P)$	1.68	0.23	[1.24, 2.12]	0.91	0.20	0.90	0.18	0.67	0.51	0.93
$AC1(D/P)$	0.76	0.10	[0.57, 0.95]	0.63	0.62	0.67	0.47	0.43	0.64	0.68
σ_D	12.53	3.07	[6.52, 18.55]	9.68	9.68	9.68	9.68	9.68	12.53	9.14

Table 4
Predictability Results

This table reports predictability of excess returns, consumption and dividend growth over one, three and five year horizons at an annual frequency for the baseline calibration in Table 1. The data sample is 1930-2013 and all coefficients and R-squared eestimates within each panel are jointly estimated using the GMM method of Hansen and Singleton (1982) and 5 Newey West lags for heteroskedasticity and autocorrelation consistent standard errors. The coefficient estimates are in units of basis points (e.g. $\beta = 0.0001$ is 0.01% or 1 basis point).

	Data				Model	
	$\hat{\beta}$	95% CI	$\hat{R}^2$	95% CI	β	R^2
	$\Pi_{j=1}^{J}(1+R_{m,t+j}-R_{f,t+j}) = \alpha + \beta PD_t + \epsilon_{t+j}$					
1Y	-0.002	[-0.004, -0.000]	0.033	[-0.033, 0.098]	-0.016	0.093
	(0.001)		(0.033)			
3Y	-0.007	[-0.012, -0.003]	0.128	[-0.029, 0.284]	-0.034	0.172
	(0.002)		(0.080)			
5Y	-0.015	[-0.022, -0.008]	0.225	[0.032, 0.418]	-0.045	0.176
	(0.004)		(0.099)			
	$\Pi_{j=1}^{J}\Delta C_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$					
1Y	0.0001	[-0.0002, 0.0005]	0.009	[-0.037, 0.056]	0.0002	0.001
	(0.0002)		(0.024)			
3Y	-0.0002	[-0.0009, 0.0006]	0.004	[-0.034, 0.043]	0.0003	0.001
	(0.0004)		(0.020)			
5Y	-0.0006	[-0.0016, 0.0003]	0.043	[-0.081, 0.167]	0.0003	0.000
	(0.0005)		(0.063)			
	$\Pi_{j=1}^{J}\Delta D_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$					
1Y	0.0013	[-0.0009, 0.0036]	0.029	[-0.045, 0.102]	0.0007	0.001
	(0.0011)		(0.037)			
3Y	0.0015	[-0.0020, 0.0051]	0.012	[-0.038, 0.062]	0.0012	0.001
	(0.0018)		(0.025)			
5Y	0.0014	[-0.0022, 0.0051]	0.011	[-0.049, 0.072]	0.0014	0.000
	(0.0018)		(0.031)			
	$PD_{t+1} = \alpha + \beta\Pi_{j=1}^{J}\Delta C_{t+1-j} + \epsilon_{t+j}$					
1Y	-3.78	[-186.83, 179.28]	0.000	[-0.002, 0.002]	-18.37	0.009
	(93.40)		(0.001)			
3Y	-35.69	[-109.63, 38.25]	0.012	[-0.037, 0.060]	-12.02	0.021
	(37.72)		(0.025)			
5Y	-55.10	[-128.94, 18.75]	0.035	[-0.060, 0.129]	-8.57	0.023
	(37.68)		(0.048)			

Table 5

Predictability Results - Alternative Calibrations

This table reports predictability of excess returns, consumption and dividend growth over one, three and five year horizons at an annual frequency for the calibrations in Table 1. The data sample is 1930-2013 and all coefficients and R-squared eestimates within each panel are jointly estimated using the GMM method of Hansen and Singleton (1982) and 5 Newey West lags for heteroskedasticity and autocorrelation consistent standard errors. Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down. Coefficient estimates are included for all calibrations in Table 37 in the Appendix.

	Data	Baseline	Baseline Special Cases (1)	(2)	(3)	(4)	Best Fit (1b)	(2b)
					$b = 0$			
			$b = 0$	$d = 0$	$d = 0$	$\rho_C = 0$	$b = 0$	$d = 0$
Time Varying Risk Aversion		Y	N	Y	N	Y	N	Y
Time Varying EIS		Y	Y	N	N	Y	Y	N

$$\Pi_{j=1}^{J}(1 + R_{m,t+j} - R_{f,t+j}) = \alpha + \beta PD_t + \epsilon_{t+j}$$

	$\hat{R}^2$	95% CI	R^2						
1Y	0.033 (0.033)	[-0.033, 0.098]	0.093	0.011	0.058	0.000	0.097	0.011	0.079
3Y	0.128 (0.080)	[-0.029, 0.284]	0.172	0.015	0.109	0.000	0.129	0.016	0.152
5Y	0.225 (0.099)	[0.032, 0.418]	0.176	0.013	0.114	0.000	0.111	0.014	0.165

$$\Pi_{j=1}^{J}\Delta C_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$$

	$\hat{R}^2$	95% CI	R^2						
1Y	0.009 (0.024)	[-0.037, 0.056]	0.001	0.000	0.125	0.221	0.000	0.001	0.118
3Y	0.004 (0.020)	[-0.034, 0.043]	0.001	0.000	0.067	0.119	0.000	0.000	0.064
5Y	0.043 (0.063)	[-0.081, 0.167]	0.000	0.000	0.040	0.071	0.000	0.000	0.038

$$\Pi_{j=1}^{J}\Delta D_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$$

	$\hat{R}^2$	95% CI	R^2						
1Y	0.029 (0.037)	[-0.045, 0.102]	0.001	0.000	0.125	0.221	0.000	0.001	0.118
3Y	0.012 (0.025)	[-0.038, 0.062]	0.001	0.000	0.067	0.118	0.000	0.000	0.063
5Y	0.011 (0.031)	[-0.049, 0.072]	0.000	0.000	0.040	0.070	0.000	0.000	0.037

$$PD_{t+1} = \alpha + \beta\Pi_{j=1}^{J}\Delta C_{t+1-j} + \epsilon_{t+j}$$

	$\hat{R}^2$	95% CI	R^2						
1Y	0.000 (0.001)	[-0.002, 0.002]	0.009	0.027	0.186	0.221	0.006	0.033	0.179
3Y	0.012 (0.025)	[-0.037, 0.060]	0.021	0.049	0.133	0.119	0.006	0.052	0.130
5Y	0.035 (0.048)	[-0.060, 0.129]	0.023	0.048	0.095	0.071	0.005	0.050	0.093

Table 6

Risk Premium Variation

This table provides the model implied risk premium and Sharpe Ratio correlations with consumption growth at an annual frequency for the baseline and alternative calibrations in Table 1. Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down.

		Baseline Special Cases				Best Fit	
		(1)	(2)	(3)	(4)	(1b)	(2b)
Moment	Baseline	$b = 0$	$d = 0$	$b = 0$, $d = 0$	$\rho_C = 0$	$b = 0$	$d = 0$
Time Varying Risk Aversion	Y	N	Y	N	Y	N	Y
Time Varying EIS	Y	Y	N	N	Y	Y	N
$\sigma(E_t(R_{m,t+1} - R_{f,t+1}))$	8.76	1.39	6.05	0.20	12.00	1.92	7.15
$\sigma(\sigma_t(R_{m,t+1} - R_{f,t+1}))$	8.02	0.87	5.04	0.25	7.29	1.81	6.39
$Corr(G_t, E_t(R_{m,t+1} - R_{f,t+1}))$	-0.20	0.16	-0.30	1.00	-0.18	-0.05	-0.33
$Corr(G_t, \sigma_t(R_{m,t+1} - R_{f,t+1}))$	-0.23	-0.04	-0.39	-1.00	-0.16	-0.28	-0.37
$Corr(G_t, SharpeRatio_t)$	-0.42	-0.46	0.79	1.00	-0.31	-0.39	0.80

Table 7

Real Term Structure

This table provides the model implied real term structure at an annual frequency for the baseline and alternative calibrations in Table 1. Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down.

Maturity			1y	2y	3y	4y	5y	6y	7y	8y	9y	10y
Yield	γ_t	ψ_t										
Baseline	Y	Y	1.47	1.58	1.63	1.66	1.67	1.67	1.66	1.65	1.64	1.62
(1) $b = 0$	N	Y	1.78	1.86	1.92	1.96	1.99	2.01	2.02	2.04	2.05	2.06
(2) $d = 0$	Y	N	2.16	2.01	1.91	1.83	1.77	1.72	1.68	1.64	1.61	1.57
(3) $b = 0, d = 0$	N	N	2.25	2.14	2.08	2.03	2.00	1.98	1.96	1.95	1.94	1.93
Best Fit												
(4) $\rho_C = 0$	Y	Y	1.31	1.61	1.75	1.83	1.87	1.89	1.89	1.89	1.89	1.88
(1b) $b = 0$	N	Y	0.71	1.01	1.21	1.34	1.43	1.50	1.56	1.60	1.63	1.66
(2b) $d = 0$	Y	N	1.57	1.43	1.33	1.25	1.18	1.12	1.07	1.03	0.99	0.95

CHAPTER 2 : Estimating the "I" in Team: The Value of Star College Football and Basketball Players.

2.1 Introduction

Collegiate athletics in the United States have been regulated by The National Collegiate Athletic Association (NCAA) since 1901.[33] One of the many, and most controversial, aspects of collegiate athletics regulated by the NCAA involves the rules on paying college athletes. Currently the NCAA restricts an athlete's compensation to in-kind transfers of institutional financial aid. The maximum amount of this "grant-in-aid" is based off the cost of attendance as calculated by each institution's financial aid office and is limited to tuition, fees, room and board, and required course-related books.[34] In addition to the rules governing institutional financial aid, the NCAA explicitly forbids outside financial aid that has any relationship to athletic ability in an effort to maintain their claims of amateurism for student-athletes.[35] As Tollison (2012) and Kahn (2007) point out, restricting competition by restricting payments to players is one of the most compelling arguments for the claim that the NCAA effectively functions as a cartel.

In a pair of recent studies, Huma and Staurowsky (2011, 2012) document a shortfall that exists between what a full athletic scholarship covers and the full cost of attending college for collegiate football players. They also estimate the average full athletic scholarship at a Division 1 FBS institutions to be worth approximately $23,204 per year. Given the fact that Division 1 FBS football programs, on average, generate millions of dollars in revenues each year while compensating players relatively little, it is not surprising that questions of fairness have recently emerged in a series of lawsuits centered around the NCAA's cartel

[33] See Tollison (2012) for an overview of the formation for the NCAA and how its purpose has shifted over time.
[34] See NCAA 2013–2014 Division I Manual, bylaw 15.02.
[35] See NCAA 2013–2014 Division I Manual, bylaws 12.1.2 and 15.01.3.

practices.

Former UCLA basketball player Ed O'Bannon brought a case against the NCAA alleging that the organization used the likeness and image of student-athletes for its own profits while prohibiting them from being paid for their efforts. On April 14, 2014, the judge presiding over the case ruled in favor of O'Bannon, allowing athletes to receive money from schools that use their names, images, and likenesses. Although the NCAA can still set a salary-cap (no lower than $5,000) and bar athletes from marketing themselves, this decision has been viewed as an important step toward breaking down the NCAA's cartel power.[36] On March 26, 2014 the United States National Labor Relations Board ruled in favor of the College Athletes Players Association (CAPA), which brought a suit against Northwestern University to establish that their football players qualify as employees of the university under federal law and should, therefore, be allowed to unionize.[37]

Most recently, an ongoing class action lawsuit filed in March 2014 against the NCAA and and the "Big 5" athletic conferences alleges these institutions function as a cartel.[38] The lawsuit claims that the NCAA's practice of price-fixing players' compensation, by allowing only full grant-in-aid, and boycotting institutions who do not comply with this rule, violates U.S. anti-trust laws under the Sherman Act. The plaintiffs in this case claim that

> The Plaintiffs—top-tier college football and men's basketball players, along with the class members whom the players seek to represent—are exploited by Defendants and their member institutions under false claims of amateurism. The Defendants and their member institutions have lost their way far down the road of commercialism, signing multi-billion dollar contracts wholly disconnected from

[36]The NCAA is currently appealing this decisons as of the time of this writing. For the full decision see *Edward C. O'Bannon v. National Collegiate Athletic Association*, 2014, 4:09-cv-03329-CW.

[37] *Northwesern University v. College Athletes Players Association*, 2014 13-RC-121359.

[38]The "Big 5" conferences named in the suit are: the Atlantic Coast Conferece, the Big 12 Conferece, the Big Ten Conference, the PAC-12 Conference, and the Southeastern Conference.

> the interests of 'student athletes,' who are barred from receiving the benefits of competitive markets for their services even though their services generate these massive revenues.[39]

The central claim here is that college athletes are directly responsible for generating millions of dollars in revenues for the institutions they play for. Furthermore, these economic rents–the difference between the revenues generated by the player and the costs associated with fielding the player–produced by players are being captured entirely by NCAA member institutions. The lawsuit's argument implies that college athletes would be able to capture a portion of these rents in the form of a market wage if they were allowed to sell their labor in a competitive labor market. Therefore, players would be compensated far beyond the value of their current compensation, which is artificially limited by the NCAA to athletic scholarships of in-kind transfers.

However, there is another side to this "pay for play" debate. In the 2013 documentary film *Schooled: The Price of College Sports*,[40] Harvey Perlman, the Chancellor of the University of Nebraska - Lincoln, is filmed saying

> I understand the criticism that they are generating all the revenue and they aren't getting any of the money and I think that is utterly false. It's because of the investments that we made, it's because of the attraction and passion that alumni have for their institution, I dont think it's because football players were playing football.

Though Mr. Perlman is not speaking on behalf of NCAA member institutions as a whole, his remarks indicate that the athletes themselves, while necessary, are not the driving force behind the large revenues being generated by these Division 1 athletics programs. The question on wether the NCAA's pay restrictions are unfair and that college athletes should

[39] *Martin Jenkins et al. v. National Collegiate Athletic Association et al.*, 2014 3:33-av-00001.
[40] Directed by Ross Finkel and Trevor Martin, produced by Makuhari Media.

be paid is a normative one. However, this paper attempts to inform this debate through a careful empirical analysis of how much college athletes are "worth" to the institutions they play for.

In a standard labor market, a natural measure of an employee's worth is how much additional revenue the employee generates for their firm. In a perfectly competitive labor market, the employee's wage would equal their marginal revenue product (MRP). Although a formal labor market for college players does not exist, estimating the MRP of the best performing "star" college players gives us an upper bound on how much the best college athletes could be paid if they were able to sell their services in a perfectly competitive labor market.[41] Also, if a labor market for college players did exist, it is likely that players would be paid less than their marginal revenue product. The size of the discrepancy would be determined by the relative bargaining power of players and universities and if players are close substitutes for one another. Nevertheless, the MRP of star players provides one useful measure of how much these stand-out players are worth to their institutions and provides a useful starting point in understanding the magnitude of the rents being captured by the NCAA's member institutions under the current pay restrictions.

In this paper I present fixed effects estimates of the MRP of star football and basketball players at Division 1 programs using a novel panel dataset spanning 2003-2012.[42] I find that football players named to the All American team are worth just over \$1.2 million a year while Heisman Finalists and Heisman Nominees are worth just over \$2.1 million and

[41] That is, of course, assuming that observed revenues would be similar to the revenues of university athletic programs under a more competitive market structure.

[42] Kahn (2007) reports that, on average, the two big revenue sports of men's basketball and football run a surplus, however, college sports as a whole report operating losses. This suggests that these two sports subsidize other athletic programs and non-athletic university expenses, which is why the literature has primarily focused on men's college football and basketball. Using the most current revenues data from the U.S. Department of Education for 2012, Men's Division 1 FBS football programs accounted for, on average, 54% of total athletic program revenues for the 123 programs contained in the data. Likiwise, men's Division 1 basketball programs accounted for, on average, just over 18% of total athletic program revenues for the 344 programs contained in the data.

$1.7 million a year respectively. I also find that having a top Quarterback, Running Back or Wide Receiver is worth around $\$600,000$ a year and that star Quarterbacks and Wide Receivers alone can be worth up to $4.6 and $2.9 million respectively. For basketball, I find that players who won the Wooden Award, Naismith Award, or were named the most outstanding player in the NCAA Tournament are worth up to $1.1 million a year while players named to the All American First Team are worth up to $\$654,000$. Also, players that were drafted, a top 5 or top 10 NBA draft pick, or were in the top 10 or 20 points scorers in a season are worth up to around $\$200,000 - \$400,000$ a year.

While the evidence suggests that star players are worth a lot to their teams, I find evidence using data from the Yahoo! Sports Rivals.com database suggesting it is difficult for recruiters to identify players ex-ante that will generate revenues above the average player on the team. I also collect data on a team's news media mentions and I find that the marginal revenue produced by these star athletes above the average player on the team tends to *decline* as the team is mentioned more frequently in the media. That is, star players seem to be worth *less* relative to the average player for teams that are mentioned more often in the media. To the extent that a team's media coverage proxies for things like a university's long term investment in the sports program or the excitement generated by the team, this finding gives some tentative support to Mr. Perlman's claim. However, overall, the results still suggest that star college football and basketball players generate a significant amount of revenue for their institutions.

The remainder of this paper is organized as follows: Section 2.2 provides an overview of the current literature estimating the MRP of college football and basketball players and discusses this paper's contributions to that literature. Section 2.3 explains the details of the revenues data, the sports statistics data, the Yahoo! Sports Rivals.com data, the data collected to measure a team's media exposure, and various other data used in the analysis.

This section also defines the various ways that star football and basketball players are measured. Section 2.4 describes the empirical strategy used to estimate a star player's marginal revenue product while Section 2.5 reports and discusses the MRP estimates. Section 2.6 presents the results from a first-difference estimation and an alternative model for revenues for robustness. Section 2.7 estimates an ex-ante star player's marginal revenue product and discusses the difference between ex-post stars that were surprise stars in college. Section 2.8 reports instrumental variables and differences-in-differences estimates using the number of injured star players for identification. Section 2.9 reports the MRP estimates for star basketball players using the Scully Method. Section 2.10 describes a model of revenues that is used to analyze how a college football or basketball team's media exposure is related to the MRP of star players and Section 2.11 concludes.

2.2 Literature Review

There are two main approaches to estimating an athlete's MRP in the current literature: the "Scully Method" and what I will call the "Direct Method". Using data on Major League Baseball players, Scully (1974) was the first to estimate an athlete's MRP. His method employs a two-step procedure that involves first, estimating individual player contributions to winning, then estimating the effect that winning has on team revenues. For the first step, he estimates a team's production function by regressing win-percentage on team inputs like pitching and batting performance. The coefficients of this estimation can be interpreted as marginal products. Step two is a regression of revenues on win-percentages and market characteristics to estimate the marginal revenue generated by winning. The MRP of baseball players is then computed by multiplying the marginal product coefficient with the marginal revenue coefficient obtained from this two-step process.

Zimbalist (1992) points out that the correct way to measure the marginal productivity of individual players should include an estimate of the marginal contribution of the replacement player the team would have chosen instead of that player. Identifying the replacement players the team would have chosen is a nearly impossible task for the econometrician. This is problematic for the Scully Method, as it relies on estimating a player's marginal productivity directly. Krautmann (1999, 2013) raises concerns that the Scully Method gives individual players on the roster full credit for team wins while ignoring the contributions of factors like coach quality and cross-player complementarities. An additional concern he raises is that the researcher's somewhat arbitrary choice of how to allocate team statistics to individual players, in calculating the player's marginal contribution to the team, represents a degree of freedom that can significantly impact the estimate of a player's marginal productivity. In light of this, he uses wages and labor contracts of professional free agent baseball players to estimate their marginal revenue product. This strategy is feasible for labor markets where a market wage exist, however, since no market wage currently exists for collegiate athletes, this approach is not viable for estimating the MRP of college players.

2.2.1 MRP Estimates of Star Football Players

Rather than compute the MRP from estimating the marginal productivity and marginal revenues separately, an alternative approach is to estimate an athlete's MRP directly from revenues data (I will refer to this as the "Direct Method"). The first paper attempting to do this for college football players was Brown (1993). He estimates the MRP of players that were chosen in the 1989–1991 National Football League (NFL) draft directly from revenues data gathered from 47 of the 101 Division 1 FBS football programs for the 1988 season.[43] As Brown points out, the skill level of the players acquired by a college team is likely to be endogenous to the team's recruiting effort, so the MRP is estimated using an instrumental variables framework. The author constructs three instruments for the number of players

[43]There are currently 120 Division 1 FBS football programs in the NCAA but only 101 at the time this paper was written.

on the team drafted into the NFL. The first instrument *Pool* is constructed by taking the number of major college players produced in each team's state relative to the number of Division 1 FBS football teams the state supports. The second instrument *Opponent Pool* is just *Pool* averaged over a team's opponents. For the third instrument, *Opponent Market*, each team's market potential is divided by their market area then this is averaged over the team's conference opponents. The market area of a team is constructed by measuring the population of each Metropolitan Statistical Area (MSA) within a 100 mile radius of each team weighted by each MSA's distance from the university. A team's market potential is measured by adding a quality index computed from cumulative point rankings to the number of other teams in the market area.

Using these three instruments, the author finds that recruiting an additional player with NFL capabilities is worth $\$538,760-\$646,150$ in annual revenues for his institution. Brown and Jewell (2004) update the estimates in Brown (1993) with more recent and extensive football program revenues data collected by the *Kansas City Star* newspaper for 87 Division 1 FBS football teams for the 1995 season. The instrumental variable methodology is the same as in Brown (1993), however, state population is used as the instrument for the number of players on a team drafted into the NFL. The instrumental variable estimation implies an additional player with NFL capabilities is worth $\$406,914$ in annual revenues for his college team.

Brown (2011), expanding the work of Brown (1993) and Brown and Jewell (2004), attempts to disentangle the effects of a football team's overall quality and individual players on revenues by estimating a player's MRP from a system of three equations in an instrumental variables framework. He uses revenue data collected by the *Indianapolis Star* newspaper for 86 Division 1 FBS football teams for the 2004 season. The author constructs three instruments for his analysis. The first instrument *Recruiting Pool* is constructed by dividing the university's state population by the number of teams in its market area, weighted by the quality of those teams.[44] The second instrument is *Academic Progress Report*, which measures the degree to which the university provides academic resources to assist student athletes. The last instrument, *Coach Salary* is just the football coach's base salary. The first equation instruments the number of NFL draftees on the team with *Recruiting Pool* and *Academic Progress Report.* The second equation instruments a measure of team performance by *Coach Salary.* The predicted values for these two equations are then used in the second stage regression of team revenues on the number of NFL draftees. Using this methodology, the author finds that the MRP of a college football player who is drafted by the NFL ranges from $\$737,528 - \$1,195,306$ in 2004, depending on what categories of revenues are included in the dependent variable.

In a more recent paper, Hunsberger and Gitter (2014) use the Scully Method to estimate the MRP of Quarterbacks in the Bowl Championship Series conferences using football program revenues data from 2004–2012 collected by the United States Department of Education. The authors use a proprietary statistic computed by ESPN called the "Total Quarterback Rating" (QBR) that attempts to account for the contribution of other players to a Quarterback's passing performance through things like sack prevention and yards after the catch. Star Quarterbacks are defined to be those with QBRs one standard deviation above the mean. The authors first estimate a Quarterback's marginal productivity by estimating the marginal effect of QBR on win probability, then multiplying the average number of games in a full season by the change in win probability that results from a change in the QBR. This marginal productivity is then multiplied by the marginal revenue of an additional win estimated from a regression of revenues on wins and other controls. Using the Scully Method in this way, the author find that star Quarterbacks are worth about $2.3 million in terms of marginal revenue product for their teams.

[44]Market area is definied to be the population of each Metropolitan Statistical Area (MSA) within a 100 mile radius of each university weighted by the distance each university is from each MSA.

2.2.2 MRP Estimates of Star Basketball Players

Very few papers have attempted to estimate the MRP of college basketball players. Brown (1994) was the first to attempt this, estimating the MRP of basketball players directly from revenues data. In his paper, the MRP of basketball players is estimated for players chosen in the 1989–1991 National Basketball Association (NBA) drafts using revenues data for the 1988 season that he gathered from 46 Division 1 men's basketball teams. Since the skill level of the players acquired by a college team is likely to be endogenous to the team's recruiting effort, he estimates the MRP using an instrumental variables framework and constructs four instruments for the number of players on the team drafted into the NBA.

For the first instrument, *Opponent Market*, each team's market potential is divided by their market area, which is then averaged over the team's opponents within their own conference. A team's market area is the population of each Metropolitan Statistical Area (MSA) within a 100 mile radius of each team weighted by each MSA's distance from the university. Market potential counts the number of other basketball teams in the team's market area and adds to this a quality index, which is computed from cumulative point rankings. The second instrument *Pool* is the number of college basketball players produced in each team's state relative to the number of Division 1 basketball teams in the state. The third instrument, *Opponent Pool*, is the average of *Pool* for the team's conference opponents. The last instrument, *Rank 85-88*, is the team's average weekly point ranking computed by aggregating their top-20 weekly rankings for the 1985–1987 seasons then dividing by the number of weeks. Using these four instruments, the author finds that recruiting an additional player with NBA capabilities is worth $\$871,310 - \$1,283,000$ in annual revenues for his college team. Brown and Jewell (2004) update the estimates in Brown (1994) with more recent and extensive basketball program revenues data collected by the *Kansas City Star* newspaper for 95 Division 1 men's basketball teams for the 1995 season. The instrumental variable methodology is the same as in Brown (1994), however, only state population is used as the instrument for the number of players on a team drafted into the NBA. The instrumental variable estimation implies an additional player with NBA capabilities is worth $1,194,469 in annual revenues for his college team.

Lane, Nagel, and Netz (2014) provides the most recent paper (and to the best of my knowledge, the only other paper) attempting to estimate a college basketball player's MRP. They use revenues data from 2001–2004 to estimate a player's MRP using the Scully Method and revenues data from 2002–2004 using the Direct Method for 169 Division 1 men's basketball teams. Using the Scully Method the authors first multiply the coefficients from a regression predicting a team's win-loss record with a player's contribution to team performance.[45] The marginal revenue of a win is then estimated and the marginal product is multiplied by the marginal revenue to compute a basketball player's MRP. They find that college basketball players are worth $91,030 on average. They also estimate the MRP of players drafted into the NBA directly from revenues using an instrumental variable approach. The authors use fifteen instruments for the number of players on the team drafted into the NBA including: the win-loss ratio; the numbers of points, goals, three-point goals, blocks, rebounds, steals, and assists per game; the percentages of goals and free throws made; whether the team was a contender or loser in the previous season; whether the head coach was new, a coach of the year, or a "winningest" coach; and a measure of the market opportunities for the school similar to that used in Brown (1993). They include team, year, and conference fixed effects along with an interaction term for "large" schools, defined to be one if a team has revenues larger than $10 million. Their results indicate that MRP for players at large schools that are eventually drafted in the NBA is $1,188,945 while the MRP for players at small schools is not statistically different from zero.

[45] A player's contribution to team performance is obtained by multiplying each player's individual performance statistics by his weight on the team, which is just his share of the overall team's statistic. Please see the paper for details regarding the statistics used.

2.2.3 Contributions to Current Literature

This paper contributes to the current literature in several ways. First, I construct a dataset containing football and basketball program revenues from the U.S. Department of Education, geographic location, and detailed performance statistics for both the teams and individual players. The dataset covers 104 Division 1 FBS college football programs and 282 Division 1 men's basketball teams spanning 2003–2012. This dataset covers many more years and athletic programs than the majority of the literature that only uses data from individual seasons. The dataset also allows for richer control variables in the empirical analyses than what has been used to date. The long panel structure and the number of athletic programs included in the dataset allows me to take advantage of both variations in revenues across time within universities and across universities to identify the effect of star college players on university revenues in estimating the MRP directly from revenues data. This panel data analysis is an important contribution to the cross-sectional analysis that comprises nearly the entirety of this literature.

Another advantage of the panel structure and estimating the MRP directly from revenues data is that I can avoid the potential problems with the Scully Method mentioned previously. In addition to these concerns, I would add that the MRP calculated using the Scully Method is a non-linear combination of random variables, which also has a distribution induced by the non-linear transformation of multiplying coefficients. As such, the standard errors of the MRP should be computed by either the Delta Method or Bootstrapping to determine if the calculated MRP is statistically significant. Researchers that employ the Scully Method never report the standard errors of the MRP and it is not sufficient to assume that the MRP will be statistically significant as long as the marginal revenue and marginal productivity estimates are statistically significant. Also, the Scully Method implicitly assumes that the only channel through which a star athlete can influence revenues is through their contribution to producing wins. In Section 2.9 I show that Scully estimates for basketball are much lower than those found using the Direct Method. This suggests that a sizable portion of player MRP comes through channels other than a star player's ability to generate wins. The direct estimation of MRP used in this paper allows for star football and basketball players to impact revenues through multiple channels and is agnostic to the mechanism through which stars are influencing revenues.

A degree of freedom that is often overlooked in this literature is how the researcher defines a "star player". The standard measure of star player in this literature is a player's NFL or NBA draft status. There are several reasons that the draft might not be the best metric to measure a player's contribution to the performance of his college team, which is discussed in more depth in Section 2.3. That said, another contribution of this paper is that my data allows me to report estimates for multiple measures of star player based on a player's actual performance in college that might more accurately reflect his ability to influence revenues in a particular year. Furthermore, while the literature has largely focused on aggregate measures (drafted players) or just Quarterbacks, this data allows me to look at more positions in football to investigate how much star players in various positions are worth to the teams they play on. In addition to the analysis of ex-post measures of star player based on performance, which is common in the literature, this paper analyzes "ex-ante" measures of stars players. This novel analysis suggests that it is difficult for college recruiters to identify players ex-ante that will generate significant revenues above those generated by the average player on their teams. This result has potential implications for how universities might prefer to compensate star athletes if they decide to compensate them beyond the current arrangement.

As previous authors have pointed out, the most likely source of endogeneity in this analysis is that the number of star players on a team might be driven by unobservable recruiting effort. Most of the literature has relied on an instrumental variable approach to solve this problem of endogeneity. However, it is unclear that the exclusion restriction holds for most of the instruments used, which is necessary for the instrumental variables estimates to be consistent. For instance, in Brown (1993, 1994) football and basketball team revenues are likely to be correlated with *Opponent Pool* in ways unrelated to the number of star players on the team as a team's opponents are not selected at random and consists largely of other teams in their conference. This is because a team's opponents are not selected at random and consist largely of other teams in their own conference. It is well known that certain conferences generate larger revenues through, for example, television contracts; these revenues will not be directly related to the number of stars on that team. In Brown and Jewell (2004), football team revenues are also likely correlated with *Academic Progress Report* and *Coach Salary*. That is, if a school has higher football revenues, they potentially have more resources to spend on improving the academic success of their football players regardless of the number of stars on the team. Likewise, the coach's salary is almost certainly correlated with team revenues in ways unrelated to the number of star players on the team since schools in wealthier conferences or with larger endowments can afford to pay higher salaries to attract good coaches independent of the number of star players they have on a team in any given year.

In the basketball studies employing instrumental variables, team revenues are also likely correlated with *Rank 85-88*. This is because players other than star players will be contributing to a team's point ranking, which will be correlated with revenues as more points means more wins and we know that wins are correlated with revenues. A similar argument holds for the fifteen instruments used in Lane et al. (2014) because these instruments measure a team's performance in ways that are indistinguishable from individual star player performances. That is, there are players other than stars on the team that are contributing to these performance measures that are correlated with winning, hence revenues, and in ways not solely through the star player's affect on revenues.[46]

[46]This problem with the exclusion restriction assumption persists even after accounting for the "included"

Perhaps more worrisome than the exclusion restriction is that the instruments used in this literature are fairly weak. As Stock, Wright, and Yogo (2002) point out, an F-statistic of above ten in the first stage regression likely means that the instruments are strong enough to assuage concerns regarding weak instruments. Although F-statistics are not reported, a back of the envelope calculation results in F-statistics for the above instruments that range from 7.32 to 7.84; the t-statistics for the instruments in the first stage regression in Brown (1994) are -0.643, -0.062, 1.50 and 3.35 while the F-statistic is 1.00 for the instrument used in Brown and Jewell (2006). Hahn and Hausman (2005) show that the problem with weak instruments is that they cause severe finite sample bias in the 2SLS estimates. This observation seems particularly relevant here given the sample sizes in the previous football studies employing 2SLS are only 39 and 86 with the previous basketball studies having sample sizes of 46 and 95. This suggests we should be concerned about potentially large finite sample bias in the MRP estimates from these studies. Although *Rank 85-88* in Brown (1994) has a t-statistic of 3.35, including three additional very weak instruments and one strong one does not solve the problem of small sample bias being generated by the other three weak instruments. Lane et al. (2014) do not report their first stage estimates and instead claim that an over-identification test confirms the validity of the instruments. However, this test implicitly assumes that both the relevance condition *and* exclusion restrictions hold for some subset of their instruments. As previously mentioned, the exclusion restriction assumption is not plausible for their excluded instruments, which are based on team performance measures.

Rather than attempt to build a better instrument to control for the potential endogeneity caused by recruiting, I rely on the richness of my dataset, which includes variables that attempt to control for a school's recruiting efforts. Furthermore, as previously mentioned,

instruments used in their regression specification.

my data suggests that a recruiter's ability to identify revenue generating skill ex-ante is limited, which should help assuage concerns over this source of potential endogeneity in the MRP estimates using OLS methods. Even after controlling for these observables, there might still be unobserved team and athletic conference characteristics driving revenues and biasing the estimates of a star player's MRP. To this end, the long panel structure of my dataset allows me to reliably control for the time-invariant unobservable characteristics using fixed effects. Ultimately, concerns over endogeneity caused by omitted variables is nearly impossible to rule out under the OLS framework. However, my dataset allows for several alternative estimation techniques and robustness checks that might help to mitigate these concerns. For instance, my data contains star players that suffered season ending injuries or suspensions, which I use in a differences-in-differences framework to estimate star player MRP. The results of this novel approach to estimating star player MRP provide tentative support for this paper's MRP estimates using OLS methods.

Finally, a novel contribution of this paper is the construction of a variable to measure the number of times a university's football or basketball team is mentioned in the news. This variable is meant to capture the "excitement" a team generates over the season as more exciting teams will generate more press coverage. This variable could also be thought of as a proxy for unobservables involving a university's long term investment in their football or basketball programs if we believe that a concerted effort by the university to improve the standing of their team is proxied for by their team's media presence. I am able to use this variable to estimate how a star player's MRP is related to their ability to generate excitement for their university's sports program and how this MRP varies for teams along the heterogeneous dimension of how often they are mentioned in the news media.

2.3 Primary Data Sources

The panel dataset used in this paper's empirical analysis is constructed using data from the various sources outlined below so that the unit of observation is the university's football or basketball team in a particular year. Since I am looking at the revenues generated by a university's football or basketball team, I will often refer to the team and the university synonymously.

2.3.1 Revenues Data

The U.S. Department of Education, under the Equity in Athletics Disclosure Act (EADA), requires all institutions with intercollegiate athletics programs that receive federal student aid funding to report their athletic program revenues. These data are collected separately each year through an online survey for revenues attributable to both men's and women's athletics across all sports offered at the institution over the academic year. For instance, these revenues data coded with calendar year 2003 are revenues generated for the academic year beginning in the fall of calendar year 2003 and ending in the spring of calendar year 2004. Although these data includes both revenues and expenditures, I am not able to use both revenues and expenditures to compute the profitability of each university's sports program. This is because the EADA survey specifies that the total reported revenues must cover total reported expenses.[47] However, since I am interested in estimating the marginal revenue product of a star player, I focus just on the reported revenues and collect revenues for each institution from 2003–2012 that are attributable to Division 1 FBS college football and Division 1 men's basketball programs.

The revenues reported in the EADA survey are for all revenues attributable to a university's

[47]See Getz and Siegfried (2012) for a discussion of how accounting for revenues and expenses in academic institutions is quite tricky, partially due to how revenues and expenditures are accounted for across different departments within an academic institution.

college football or basketball program and includes: revenues from appearance guarantees and options, an athletic conference, tournament or bowl games, concessions, contributions from alumni and others, fund-raising activities, institutional support, program advertising and sales, radio and television, royalties, signage and other sponsorships, sports camps, state or other government support, student activity fees, ticket and luxury box sales. Revenues include more than earned income, such as gate receipts, and the basis for determining whether revenue should be included is simply whether the item was attributable to the university's football or basketball program activities. Furthermore, these reported revenues are actual amounts earned or received, not pledged, budgeted, or estimated amounts. What is *not* included in the revenues data are capital assets and related debts (i.e. money specifically identified to pay for capital assets) or money for indirect facilities.

The advantage of using these revenues data is that they are available over a long time horizon for the entirety of universities fielding Division 1 FBS football and Division 1 men's basketball teams and they include a comprehensive list of revenue sources. The downside of using these data is that revenues are not reported by category so that only an aggregate revenue measure is available. Brown (2011) uses college football program revenues collected by the *Indianapolis Star* for the 2004-2005 season that are disaggregated into categories like ticket sales, game day sales, contributions, and NCAA conference distributions that he claims are more likely associated with the quality of a team's *current* players. His contention is that if the aggregate revenues measure includes things like students fees, government and institutional aid or endowment/investment income that are associated with past team quality and less dependent on the quality of the team's current players, then the analysis might overstate the effect of current players on team revenues. This observation is likely correct although, given the panel structure of my data, these concerns can easily be controlled for by including measures of past team performance as well as year, conference, and team fixed effects. This is not possible with the *Indianapolis Star* data that only covers one season, limiting the analysis to the cross-section.

Finally, revenues are reported in nominal U.S. dollars and I convert them to real 2012 U.S. dollars using the headline Consumer Price Index for all urban consumers computed by the Bureau of Labor Statistics. Tables 8 and 9 report summary statistics for football and basketball program revenues, along with other variables used in the empirical analysis. From the tables we see that the average Division 1 FBS football program over the sample 2003–2012 generated almost $24 million dollars in annual revenues with average revenues for 90% of teams being less than $55 million. Not surprisingly, the revenue distribution is right-skewed as a few teams generate very large revenues. For instance, the University of Texas at Austin tops the list with just over $111 million in 2012. Likewise, over 2003–2012, the average Division 1 men's basketball program generated almost $4 million dollars in annual revenues with average revenues for 90% of teams being less than about $10 million. As with football program revenues, the revenue distribution for basketball programs is right-skewed with a few teams generating very large revenues. The University of Louisville's basketball program tops the list with just over $44 million in revenues for 2011.

2.3.2 Sports Statistics Data

For each academic year and the 104 Division 1 FBS football programs that I have revenues data for, I collect team performance statistics from Sports Reference.[48,49] Particular statistics of interest that will be used to construct control variables for the empirical identification strategy are: wins, the current coach, the team's bowl game appearances and performance, and the team's schedule strength.[50] Several measures of the team's defense quality are also collected including: points allowed per game, total yards allowed per game,

[48] Each academic year corresponds to the football or basketball season over the same time period.

[49] Sports Reference LLC. 6757 Greene St. Suite 315 Philadelphia, PA 19119. The football data are accessed from http://www.sports-reference.com/cfb/, while the basketball data are accessed from http://www.sports-reference.com/cbb/.

[50] This statistic is denominated in points above or below average where zero is the average. For details on how schedule strength is computed for football, please see http://www.sports-reference.com/cfb/about/glossary.html.

passing and rushing yards allowed per game, and passing and rushing touchdowns allowed per game. The Sports Reference website also contains historical information on each college football coach's win record over their entire career, which are collected and included with the team performance data. In addition to team level data, I collect performance statistics for $25,221$ individual football players over the 2003-2012 sample period. These data include the number of games played by each player in each season along with various performance statistics like touchdowns and yards for offensive players and accolades such as if the player was voted to the All-American Team or nominated for the Heisman Trophy.

I also collect team performance statistics from Sports Reference for each season and for each of the 282 Division 1 men's college basketball programs that I have revenues data for. In particular, I collect: wins; the current coach; the team's NCAA tournament appearances and performance; the number of teams in each athletic conference that are ranked by the Associated Press in the NCAA tournament that year, their tournament performance, and the total number of teams in each conference; and the team's schedule strength.[51] The Sports Reference website also has historical information for each college basketball coach's win record and NCAA Tournament appearances over their entire career, which are collected and included with the team performance data. In addition to team performance data, I collect performance statistics for $18,855$ individual basketball players over the 2003–2012 sample period. These data include the number of games played by each player in each season, the number of points scored by each player in a season and accolades such as if the player was voted to the All American First or Second Teams, was awarded the Naismith or Wooden Awards, or named most outstanding player in the NCAA Tournament.

[51]For details on how schedule strength is computed for basketball, please see http://www.sports-reference.com/cbb/about/glossary.html.

2.3.3 Star Player Measures

If we are interested in measuring a college athelete's MRP to inform the debate on whether or not college athletes are being unfairly exploited, we need a way to separate an individual player's contribution from the team's contribution to revenues. Conceptually this is a difficult task since a football or basketball team is a collection of individuals whose direct individual performances and complementarities with the performance of their teammates all influence the team's ability to generate revenue. One way we might attempt to distinguish between the individual player and the team is to focus the analysis on exceptionally good players measured by some metric of performance. While this will not allow us to estimate the MRP of an average player on the team, focusing on the very best players that would command the highest wages in a competitive labor market will give us an upper bound on the economic rents being extracted from players by NCAA member institutions.

Star Football Player Measures

I construct six different measures of star player using performance statistics for 25,221 individual football players. The first measure is if the player was selected to the consensus All-American Team. Selection to the consensus All-American team is an honor given each year to the best college football players at their respective positions. Selection to the team is recognized by the NCAA and determined by a group of selector organizations.[52] The All-American measure of star allows me to measure star players across *all positions* in football since the best player in each position are voted to the All-American team. The second and third measures are if a player was a Heisman Trophy finalist or nominated for the Heisman Trophy. The Heisman Trophy is an award given each year to the most outstanding player in college football. Selection for the Heisman is determined by sports journalists,

[52]Since 2009, the full list of selector organizations are: Associated Press, Football Writers Association of America, American Football Coaches Association, Walter Camp Foundation and The Sporting News. If three of these organizations select a player, he automatically receives the consensus honor.

previous Heisman winners, and a fan survey collected by ESPN.[53] Typically, around ten players each year are nominated for the Heisman Trophy and I have defined a finalist as a player who finished in the top five or better in the Heisman voting among all players who were nominated. Unlike the All-American team measure, these measures are restricted to Quarterbacks, Running Backs, and Wide Receivers since these positions make up 90% of all positions nominated for the Heisman over the period 2003-2012.[54]

The last three measures of star player are computed from individual player performance statistics. One downside to using performance statistics is that there is not very good data coverage for positions other than Quarterbacks, Running Backs, and Wide Receivers. Although this may seem like a limitation, it may also imply that these are the positions that people focus their attention on. So to the extent that star players are able to generate revenues through their salience to fans, it is likely that not much is lost by focusing on these positions here. In determining how to measure star players based on performance, I choose to focus on touchdowns scored and yards generated because these are likely to be the more visible metrics that directly impact a team's ability to win games, play in lucrative bowl games, and generate fan excitement. Hence, the fourth measure of star player is if a Quarterback, Running Back or Wide Receiver was among the top 10 players in scoring touchdowns *or* generating yards within their position for that season. I choose the simple rule for being in the top 10 in one or the other category (or both) to avoid having to arbitrarily pick relative weights in combining statistics, which would otherwise be needed for an index measure to rank players according to multiple statistics.

The last two measures of star player are the same for Running Backs and Wide Receivers (top 10 in touchdowns or yards) but changes how star Quarterbacks are defined. The fifth

[53]For detailed information of the balloting and selection process please see http://heisman.com/sports/2014/9/15/GEN_0915140346.aspx?.

[54]There are a total of five Defensive Linemen, four Linebackers and one Defensive Back nominated over the ten years in the sample.

measure designates a Quarterback as a star if they are among the top 10 Quarterbacks in touchdowns, or yards, or in their pass efficiency rating (PER). The PER is a common metric used in sports statistics to rank Quarterbacks by taking into account interceptions, pass completions, and pass attempts in addition to yards and touchdowns.[55] The sixth measure designates a Quarterback as a star if they are among the top 10 Quarterbacks ranked only by their PER rating.

Table 10 gives a sense of how rare these star players are over the sample period for each definition of star player. For example, All-American players make up just under 0.5% of all players while Heisman Finalists are the most rare with only 0.08%. Among Quarterbacks, All-American Quarterbacks are the most rare (0.37%) since there are only 11 of them chosen whereas Quarterbacks are overrepresented among players nominated for the Heisman Trophy.[56] Even for the most permissive category (5), star players comprise about only 1% of all players and 3% of all Quarterbacks, Running Backs, and Wide Receivers. Also, only 6% of Quarterbacks are designated as star players under measure (5) while star Running Backs and Wide Receivers comprise 2.5% and 2% of players in their positions. Although how one defines a star player is somewhat subjective, the purpose of presenting multiple measures is to see how estimates of the MRP change depending on the definition since the question under consideration is relative to how star players are defined.

While the previous literature has primarily focused on future NFL draftee status to define a star college football player, I prefer the measures in Table 10 for several reasons. First, these measures of star player are better able to capture a player's potential contribution to team revenues in each year they played for the team. Strictly speaking, the NFL Draft reflects professional scout expectations of future performance at the professional level verses

[55]The forumula is $(8.4 \times Yards + 330 \times Touchdowns - 200 \times Interceptions + 100 \times Completions)/Attempts$.

[56]Typically there is just one All-American Quarterback per year, however, the reason there are 11 and not 10 is that there were two Quarterbacks chosen in 2008 as the six selector organizations were equally divided over Sam Bradford and Colt McCoy.

the player's actual performance in college relative to their peers in a given year. Hence, draft status is not directly connected to a player's performance in a particular year in which they might be contributing to school revenues other than in the season immediately before they were drafted.[57] There are also cases of outstanding college athletes that do not fare well in the NFL draft. For example, Oklahoma quarterback Jason White won the Heisman in 2003 and led his team to the national championship but was not selected in the NFL draft.[58] Even more problematic is that NFL draft status may have less to do with college performance than we think. Berri and Simmons (2011) looked at 121 quarterbacks from 1999–2008 and found that nearly 20% of the variation in Quarterback draft position is explained by just the NFL combine factors.[59] When performance measures like wins produced, net points and Quarterback score are added explanatory power only rises less than 3%. Overall they find that combine factors appear to be more important than the actual college performance of the Quarterbacks in terms of NFL draft pick.

The six measures of star football player just mentioned are "discrete" in the sense that they do not account for the fact that there might be variation in how much stars are contributing to a team's revenues. For instance, suppose two players are among the top 10 players in touchdowns or yards in a given year but one only played in half their team's games while the other played in all their team's games that season. The current discrete measures will treat these two players as identical since the star designation is binary. However, my dataset contains the number of games played by each player as well as the number of games played by the team in a given season. Therefore, the richness of my dataset allows me to compute a more precise "continuous" measure of star player by multiplying the binary star designation by the proportion of games played by that star player in that season. So

[57] Alternatively, I could use the NFL draft to designate a player as a star for *every* year they played college football if they were drafted in their last year. However, if star players actually have an effect on revenues such that revenues are higher when a team has a star player, this measure will likely underestimate a star players effect on revenues as he will be mechanically designated a star player in years of low or average revenues independent of his performance in that year.

[58] Hunsberger and Gitter (2014) page 4.

[59] The NFL combine factors examined were height, weight, Wonderlic score, and 40 yard dash times.

in the previous example, one team would have 0.5 of a star player while the other team would have 1 star player. Likewise, if one team had three star players, one of which only played in 75% of the games that season, the team would have 2.75 star players under this continuous measure rather than 3. This continuous measure is more precise in allowing for a star player's contribution to team revenues in a season than the discrete measure. The continuous measure also allows for more variation in the number of star players on a team, which will result in more precise estimates of a star player's MRP.[60]

Star Basketball Player Measures

Using the performance statistics for 18,855 individual basketball players I construct eight different measures of star player. The first measure (Award Winners) is if the player was named most outstanding player in the NCAA Tournament, or won the Naismith Award, or won the Wooden Award. The most outstanding player in the NCAA Tournament is selected by the Associated Press for their performance over the course of the tournament and need not always be on the winning team. The Naismith Award is given by the Atlanta Tipoff Club to the top men's college basketball player each year, as selected by a committee of sports media outlets.[61] Another annual award recognizing the most outstanding men's college basketball player is the Wooden Award, given by the Los Angeles Athletic Club.[62] The second measure of star player is if the player was selected to the consensus All-American first team while the third measure is if the player was selected to the consensus All-American first or second teams. Selection to the consensus All-American teams is recognized by the NCAA and is an honor given each year to the best college basketball players, determined by a group of selector organizations.[63] The fourth measure is if a player was selected in the

[60] Unless explicitly noted, the continuous measure of star player will be used.

[61] For detailed information regarding the selection committe and selection process please see http://www.naismithtrophy.com/about/atlanta-tipoff-club/board-of-selectors/.

[62] For detailed information regarding the selection process please see http://www.woodenaward.com/about.

[63] The full list of selector organizations are: the Associated Press, the United States Basketball Writers Association, the Sporting News, and the National Association of Basketball Coaches. Each selector chooses a first and second team and consensus teams are determined by aggregating the results as determined by

NBA draft while the fifth and sixth measures are if the player was among the top five and top ten NBA draft picks respectively. The last two measures of star player are computed from individual player performance statistics and designate a player as a star if he was ranked among the top 10 or top 20 players in total points scored in that season.

As mentioned above, the previous literature has focused on NBA draft status to define a star college basketball player. However, as with the NFL draft, it is not clear this is the best measure of college performance since the NBA Draft reflects professional scout expectations of future performance at the professional level rather than the player's actual performance in college relative to their peers in a given year. Therefore, player's performance in a particular year where they might be contributing to revenues will not necessarily be captured by their NBA draft status. The alternative star player measures in Table 11 are better able to capture a player's potential contribution to basketball team revenues in each year they played for their college team because, in *any* given season over their collegiate career, a player may or may not be designated a star according to these metrics. In the absence of empirical studies citing the questionable linkage between draft status and college performance that exists in football for basketball, I include NBA draft based star player measures to provide comparisons with the previous literature. Table 11 reports how few of these star players there are over the sample period. For example, the rarest group, Award Winners, make up just 0.05% of all players while drafted players, at 1.06% of all players, are the most common. As with football, I construct the continuous star measure counterpart for all eight basketball star player measures by multiplying the discrete star player designation by the percentage of games played by that star in that season.

the NCAA.

2.3.4 Yahoo! Sports Rivals.com Data

Each year, Yahoo! Sports collects information on the top high school football and basketball prospects and ranks them in their Rivals.com database.[64] The measures of star player discussed in the previous sections are all ex-post measures, which are based from realized performance. However, because Rivals.com ranks players before they enter college, the Rivals.com ranking allows me to construct ex-ante measures of star player that are based on a player's expected performance in college. For all football and basketball players from 2003–2012 in the Rivals.com database, I collected the rank assigned to them by Rivals.com and matched these data with the individual data collected from Sports Reference. Since there is no unique identifier mapping between these two data sources, players were matched based on the year, their name, and the school they signed with. Since there was some differences with name spellings between the two datasets, a fuzzy match was also conducted and then checked by hand to prevent erroneous matches. In the end, I was able to match $16,104$ of the $25,221$ individual football players and $9,982$ of the $18,855$ individual basketball players in the Sport Reference data with their Rivals.com information.

The rankings published by Rivals.com are compiled by professional recruiting analysts with both national and regional experts who evaluate hours of film and combine input from professional, college, and high school coaches with personal observations to rank players according to their expected impact in college sports. The Rivals.com ranking system ranks prospects on a numerical scale from $4.9 - 6.1$ with 6.1 denoting a "franchise player", who is considered one of the "elite of the elite" prospects in the country. For football, these are players generally considered among the nation's top 25 players overall and deemed to have excellent professional potential. For basketball, these are players who are expected to be college superstars, an upper-end lottery draft pick after one year of college. Football recruits ranked with a 6.0 are those expected to be All-American candidates, considered

[64]The Yahoo! Rivals.com data can be accessed at: https://rivals.yahoo.com.

one of the nation's top 300 prospects, and deemed to have professional potential with the ability to make an impact on a college team. Basketball recruits ranked with a 6.0 are elite prospects who are expected to dominate in college and pegged as a first-round draft pick after a year or two in college. Rivals.com also provide an alternative star ranking to the numerical one, with a five-star prospect denoting a player who is generally considered to be one of the nation's top 25-30 players.

I use these Rivals.com rankings to construct three ex-ante measures of football stars: Top Rivals, which includes any player with a Rival.com rank of 6.1, High Rivals, which includes any player with a Rival.com rank of 6.0 or better, and 5 Star, which includes any player with a 5-star Rivals.com rating. For basketball, I only construct one ex-ante measure using the Rivals.com 5-star ranking since the number of players ranked by the numerical Rivals.com ranking are extremely sparse in my matched sample. Also, although the Rivals.com data starts in 2003, I only use data for 2005-2012 as the number of ex-ante stars designated in my matched sample for years prior to 2005 is sparse and fluctuates much more than in the later years. Since I want to make sure that my results are not being biased by the mechanical lack of ex-ante star players observed in these earlier years, I restrict the ex-ante analyses to the 2005-2012 period. The relative frequency of ex-ante stars under these measures are reported in Table 12 over the sample period 2005-2012. When comparing these relative frequencies with those in Tables 10 and 11, we see that the ex-ante measures are less rare than the ex-post measures. However, these ex-ante measures are as restrictive as possible given how Rivals.com ranks recruits.

2.3.5 Distance and Regional Data

In the empirical strategy outlined in the following section, it will be useful to control for the distance that each university is from the pool of talented players that it could potentially recruit in a given year. Included in the Rivals.com data I collected is each football and basketball recruit's hometown and/or where they went to high school. I used the 2013 National Places Gazetteer files from the United States Census Bureau to get the latitude and longitude coordinates for each university's location and for where individual players went to high school.[65] Since the players listed in the Rivals.com data are the top high school recruits each year, the college players in the Sports Reference data for which I have latitude and longitude information represent the pool of players thought to be "good" at the time they were being recruited by colleges. I use these latitudes and longitudes to compute the distance that each player was from each university for each year. These distances are then averaged across players within a year for each university. This calculated measure gives the average distance in a given year that each university is from where college players *in that year* went to high school that were considered top high school recruits.

Additional data is collected on the undergraduate population of each university from the EADA database and the university's city and state populations from the United States Census Bureau's historical population estimates to control for a team's potential market size and market demand. I also collect per-capita personal income for each university's state from the Bureau of Economic Analysis' (BEA) Regional Personal Income Data and convert these nominal values to Real 2012 U.S. dollars using the BEA's personal consumption expenditure price index for all goods and services.[66]

2.3.6 News Media Mentions

In an attempt to capture how a star player's ability to generate "excitement" might relate to their MRP, I collect data on the number of times a football or basketball team is men-

[65]The lattitude and longitudes for any towns or cities listed for players in the Rivals.com data that did not show up as an official place in the Gazetteer files were searched by hand using Google Maps at http://maps.google.com.

[66]Personal income data come from BEA Regional Accounts Tables: SA1-3 Personal Income Summary while the price index is from BEA NIPA Table: 2.3.4 - Price Indexes for Personal Consumption Expenditures by Major Type of Product.

tioned in the news from the Newsbank Access World News database. Newsbank's database contains eleven source types including audio, blog, university newspapers, journals, magazines, newsletters, newspapers, newswire, transcripts, video, and web-only sources for $4,533$ different publications across the world. The entire universe of publications and sources was queried for any mention of the university's football team and the number of "hits" was collected to count the number of media mentions the team had in that year. Newsbank's web-based interface allows for multiple search fields; for instance, if "2012" was entered in the "Year" field and " "Texas A&M" + "college football" " was entered in the "All Text" field, then the number of results returned represent an entry published in 2012 in any of the eleven source types across the universe of publications that mentions the phrases "Texas A&M" and "college football".

Colloquial team names were used in the search queries rather than official university titles. For example, "UCLA" and "UNC" were used rather than "The University of California at Los Angeles" and "University of North Carolina". This provided a challenge for teams whose colloquial names are the same as a state and/or have words in common with other college teams. Take, for instance, the University of Texas at Austin using their colloquial name "Texas" to search for news mentions using "Texas" + "college football". To help prevent hits coming back that mention the *state* of Texas or any of the other Division 1 FBS college football teams located in Texas with the word "Texas" in their name, the search query used was: "Texas - Christian - A&M - Tech" + "college football".[67]

Tables 8 and 9 gives summary statistics for the number of news mentions. Although the distribution in both cases is right-skewed, the magnitude of the largest value for football $(7,368)$ was in 2010 for the University of Auburn. This was the season when Cam New-

[67] One might think to search by the team's mascot, for instance, "Longhorns" or "Texas Longhorns". This was tested out and seemed to produce far too few results. Specific details about the search method are available from the author upon request.

ton was the Quarterback and Auburn went undefeated in the regular season, beat South Carolina for the SEC Championship game, and beat Oregon in the BCS National Championship Game. That this year and team resulted in the most news mentions is consistent with the buzz surrounding Cam Newton combined with the newsworthy accomplishment of going undefeated in both the regular and post seasons that culminated with a national championship win. For basketball, the largest value ($3,946$) was in 2012-13 for the University of Louisville, which won the NCAA tournament that year with a school record 35 wins that season. Other notable events for Louisville that season were a loss to Notre Dame in a five over-time game (the longest regular season game in their athletic conference's history) and Louisville guard Kevin Ware suffering a compound fracture in their NCAA tournament regional-final game against Duke; Louisville went on to come from behind and beat Duke by 22 points. Furthermore, while the number of news hits for Auburn and Louisville seem very large relative to the distribution, they are not extreme outliers. Inspecting the football and basketball teams that are in the right tail of the news distribution reveals well known teams that would be expected to be mentioned frequently in the news. This indicates that the news measure probably is not picking up erroneous news mentions by, for example, grabbing all entries with the word "Texas" in them that have little or nothing to do with college football (basketball) or specifically with the University of Texas' football (basketball) team. Of course, it is impossible to guarantee that every resulting entry is directly commenting on a particular football or basketball team, however, great care was taken to make sure the queries were as accurate as possible so that the number of news hits provides a reasonable proxy measure for the frequency of media mentions the team is getting in a given year.

2.4 Empirical Strategy

The empirical strategy employed in this paper is to estimate the MRP of star college athletes directly from football and basketball program revenues data. This approach avoids the concerns with the Scully Method previously discussed because it does not require direct estimates of the team's marginal revenues nor a player's marginal productivity. Furthermore, the Scully Method assumes that the only way star players can influence revenues is through their contribution to producing wins and ignores factors such as star players generating excitement for their teams in ways unrelated directly to the team winning. The empirical strategy employed here provides more flexibility by allowing for other potential channels through which star players might affect revenues and is agnostic to the particular mechanism at work.

There are many team characteristics that cannot be directly observed by the econometrician that are likely to be correlated with the team's football and basketball revenues. For instance, a team's athletic legacy or a vibrant sporting culture associated with either a particular team or the team's surrounding geographic region probably impacts the team's ability to generate revenues. Likewise, unobserved characteristics of particular years or athletic conferences might be correlated with the team's football or basketball revenues in ways that are not necessarily related to the number of star players on the team. Without accounting for these effects, the ability of the econometric analysis to detect a star player's true contribution to revenues is likely to be confounded. Fortunately, the panel nature of my data allows for these unobservable characteristics to be controlled for, which has not been possible in the previous studies that focus solely on the cross-section of teams in a particular season. Also, in contrast to previous studies on basketball using a panel dataset with only three years, the length of my panel data mitigates concerns over potential bias in the fixed effects estimation coming through the short time dimension.

2.4.1 Econometric Specification

Consider the following reduced form model relating athletic program revenues to the number of star players on the team

$$y_{i,t} = \beta Star_{i,t} + X_{i,t}\gamma + \theta_i t + \delta_t + \delta_c + \delta_i + \epsilon_{i,t} \tag{2.1}$$

where the level of football or basketball program revenues $y_{i,t}$ for team i in year t is a function of: the number of star players on the team $Star_{i,t}$; a vector of variables $X_{i,t}$ influencing revenues; a team specific linear trend $\theta_i t$; and unobserved year δ_t, athletic conference δ_c, and team characteristics δ_i. The economic motivation behind choosing the functional form of Equation (2.1) and using levels of program revenues is that the coefficient β has the direct interpretation of a star player's marginal revenue product.

To take advantage of the panel structure of my data, I estimate a star player's MRP from Equation (2.1) using a fixed effects specification including team, year, and athletic conference fixed effects. Year fixed effects will help control for trends in revenues that are unrelated to star players. For instance, if a team's conference renegotiates their revenue sharing agreement or a team signs a lucrative televisions rights deal in a particular year over the sample period. The athletic conference fixed effect controls for the fact that some conferences, like the Big 5, are much more lucrative than others. Also included is a linear trend for each team ($\gamma_i t$) to allow for heterogeneity in revenue trend rates. For the estimates of a star's MRP to have a casual interpretation, the fixed effect specification requires the strict exogeneity assumption, $E(Star_{i,t}, \epsilon_{s,t}) \neq 0$ for $s = t, t-1, \ldots$, which rules out feedback from past $\epsilon_{i,s}$ shocks to current $Star_{i,t}$. It is worth noting that the implied counterfactual of the estimate $\hat{\beta}$ under this empirical strategy is the additional revenue a team would have collected if they had an additional star player, relative to an average player *on that team*. That is, since I am using team fixed effects, the counterfactual is relative to the average player that a particular team would have had, rather than the average college football player across all teams.

In addition to the fixed-effects, I include several control variables in the regression analysis in an attempt to control for potential endogeneity. One and two year lags of $Star_{i,t}$ are included to control for any residual effect that star players have on revenues. For example, Texas A&M's season ticket sales might increase for a season or two after Johnny Manziel leaves the team due to residual excitement he generated for Texas A&M football. Likewise, I include one and two year lags of the number of wins ($Wins_{i,t-1}$, $Wins_{i,t-2}$) to control for the residual effects of the team's recent performance on revenues. I also include several variables to control for the potential market size and market demand for a team's football or basketball program. These include the size of the undergraduate student body ($UndergradPop_{i,t}$), city and state populations where the team resides ($CityPop_{i,t}$, $StatePop_{i,t}$), per-capita personal income in the state where the team resides ($PerCapPI_{i,t}$), and the growth rate of the state's per-capita income ($GrPerCapPI_{i,t}$).

Football Controls

For the MRP estimates of star college football players from Equation (2.1), I include controls for if the team went to a bowl game or won a bowl game last season ($BowlGame_{i,t-1}$, $BowlWin_{i,t-1}$). I also include two variables to control for the football coach's impact on revenues. The first is an indicator, $CoachChange_{i,t}$, which takes the value of 1 if the team had a new coach that year. I want to include a control for coach quality, however, it is difficult to disentangle coach quality from team quality with team level statistics such as win-loss record since the team's record is the coach's record over a given season. Since I have data on coach performance from Sports Reference that precedes my 2003–2012 sample for revenues data and since coaches change teams frequently, I am able to measure performance of coaches over their entire careers. So I include the win percentage of the team's *current* coach (in year t) over his entire career up to and including the previous season

($CoachCareer_{i,t-1}$).

Completely disentangling an individual star player's contribution from the rest of the team is very difficult. In fact, great care must be taken when attempting to control for the team's quality that no variables are included that could themselves be outcomes of the number of stars on a team. These variables would be bad controls and introduce bias into the MRP estimates. For instance, including the number of wins in the current season is a bad control since star players in that year are going to be directly contributing to wins. Fortunately, with football, it is possible to partially control for team quality in the regressions that use star measures 2–6 by including variables that measure the quality of a team's defense. This is because the aggregate star measures 2–6 only include the offensive positions Quarterback, Running Back, and Wide Receiver. So I include the number of points allowed ($TDPts_{i,t}$), the number of yards allowed ($TDYds_{i,t}$), the number of passing yards allowed ($TDPassYds_{i,t}$), the number of passing touchdowns allowed ($TDPassTDs_{i,t}$), the number of rushing yards allowed ($TDRushYds_{i,t}$) and the number of rushing touchdowns allowed ($TDRushTDs_{i,t}$).[68] Note that these team defense variables are bad controls in the regression using the All-American measure since both offensive and defensive positions are included in that measure, so I omit them in that regression. I also include a measure of how strong the team's schedule is ($SOS_{i,t}$) as the quality of a team's opponents likely affects their ability to generate revenues in that season.[69]

Basketball Controls

For the MRP estimates of star college basketball players from Equation (2.1), I include controls for if the team went to the NCAA Tournament last season ($NCAATourn_{i,t-1}$) and if the team made it to the second round ($Round2_{i,t-1}$), the sweet sixteen ($Sweet16_{i,t-1}$),

[68]The prefix "TD" in the variable names denotes "Team Defense".

[69]The details of this strength of schedule measure are described in Section 2.3

the elite eight ($Elite8_{i,t-1}$), the final four ($Final4_{i,t-1}$), the final ($Final_{i,t-1}$), or won the tournament ($Winner_{i,t-1}$). As with football, I control for the basketball coach's impact on revenues using $CoachChange_{i,t}$ and $CoachCareer_{i,t-1}$, however, the basketball data allows me to include an additional control $CoachCarTourn_{i,t-1}$. This additional control variable for coach quality measures number of times the coach has taken a team to the NCAA tournament in his career up to an including the previous season.

Being selected as one of the 68 teams in the NCAA Tournament is quite lucrative for these college basketball teams. The 32 teams that win their conference championship are automatically admitted to the tournament while the 36 remaining slots are given to teams by a selection committee comprised of athletic directors and conference commissioners. The committee selects the remaining teams based on national ranking polls and various other performance measures. This means that the strength of a team's athletic conference in a given year is directly related to the likelihood that a team attends the NCAA tournament, hence correlated with team revenues. To control for this, I include several variables that attempt to measure how competitive a team's conference is including: the number of other teams in the conference ($NSchlsConf_{i,t}$), the number of conference teams ranked in the AP poll ($NSchlsConfAP_{i,t}$), the number of conference teams in the NCAA Tournament that year ($NSchlsConfTourn_{i,t}$) and the number of conference teams that made it to the final four that year ($NSchlsConfFF_{i,t}$). As with football, I also control for the quality of a team's opponents using the team's schedule strength ($SOS_{i,t}$).

2.4.2 Recruiting Effort

The skill level of players acquired by a college team is likely to be endogenous to its recruiting effort, which is unobserved by the econometrician, so that the number of star players would likely be correlated with the error term in Equation (2.1). The recruiting process potentially creates a two-sided selection problem where we might be concerned that teams with high revenues can afford to expend more effort to recruit better players and that better players might select teams that historically generate higher revenues, even holding recruiting effort constant. For basketball, this selection issue might be particularly acute for student athletes already out of high school that transfer from one college to another, as their ability to play college basketball has likely been revealed to a greater extent than a student being recruited directly from high school. Transferring schools is not uncommon in college basketball (and to a much lesser extend in football) and since my data allows me to identify transfer students, I exclude them when designating star players to reduce the potential for selection bias.

In theory, the relationship between recruiting effort and revenues should be mitigated by the NCAA's strict recruiting rules that attempt to level the playing field for recruiters.[70] Nevertheless, recruiting effort and how it relates to revenues is still unobservable in the data and detection of rule violations is far from perfect. If we assume that the recruiting effort at each university is roughly a constant proportion of revenues–the additional amount spent on recruiting rises proportionally with revenues at a constant rate over time–then this selection should not bias the estimates very much because I can control for trends in revenues with year fixed effects and school specific time trends. However, selection in the other direction might still be a problem since naturally good players might choose better teams that generate higher revenues. I can potentially control for this if selection is based on factors I can observe in the data. Dumond, Lynch, and Platania (2008) show that a high school football recruit's decisions are governed primarily by three factors: geographic distance between the recruit and the college, the school's recent football rankings and if the school is in one of the BCS conferences. In particular, the authors find that recruits tend to choose programs that are closer to where they are from, so I control for this with the variable $Distance_{i,t}$, which is the average distance in a given year that each university is from where college players *in that year* went to high school that were considered top high school recruits.

[70] See NCAA 2013-2014 Division I Manual, bylaw 13.01.

To account for the fact that college football players selected schools based on the school's recent football rankings (performance) at the time they were making their decision, I construct three variables: $HistWins_{i,t}$, $HistBowls_{i,t}$, and $HistBowlWins_{i,t}$. The variable $HistWins_{i,t}$ computes the average number of wins the team had over the five years *4 years prior* to the current year. For example, the variable value for 2003 measures the average number of wins the team had over the period 1995–1999. So for college football stars in 2003 that are in their Senior year, this variable measures their current team's average number of wins over the time they were in high school plus one year prior to high school.[71] The variables $HistBowls_{i,t}$ and $HistBowlWins_{i,t}$ are constructed in the analogous way for the total number of bowl game appearances and bowl game wins. These variables are meant to capture the information set that star college players had in terms of the team's recent performance when they were being recruited out of high school.

While the Dumond et al. (2008) study was done specifically for football players, it seems reasonable to assume that the salient set of characteristics governing a player's preferences and choice of where to play in college would be the same for basketball players. So to control explicitly for the factors that drive a student athlete's choice of school in the basketball analysis, I include the variables $Distance_{i,t}$ and $HistWins_{i,t}$. I also construct several variables to control for basketball players selecting schools based on recent performance. The variables $HistNCAATourn_{i,t}$, $HistRound2_{i,t}$, $HistSweet16_{i,t}$, $HistElite8_{i,t}$, $HistFinal4_{i,t}$, $HistFinal_{i,t}$ and $HistWinner_{i,t}$ are constructed analogously to the variable $HistWins_{i,t}$ for the team's total number of appearances in: the NCAA Tournament, the second round, the sweet sixteen, the elite eight, the final four, the final and the number of times the team won the tournament. As with football, these variables are meant to capture

[71] On the other end of the spectrum, for Freshman star players in 2003, this variable measures their current team's average number of wins over the time they were freshmen in high school back into junior high school. However, the vast majority of star players in the data are college Seniors and Juniors.

the information set that star college basketball players had regarding their team's recent performance at the time they were being recruited out of high school.

2.4.3 Discussion

As with any fixed effects identification strategy we should be concerned with the potential for reverse causality and omitted variables bias to confound any causal interpretation of the coefficient estimates. In this context, reverse causality would imply that football or basketball program revenues generated in the *current* season are able to turn players into stars *in that season* according to the ex-post performance measures used to define star players. For instance, if teams have idiosyncratically high revenues over a particular season and then used these revenues to develop player talents over that season, then we should be worried about reverse causality.

However, there are two reasons why reverse causality should not be too worrisome in this context. First, we would have to believe that a team is able to spend current revenues in such a way as to make a marginal player into a star player. In reality, it is more likely that a player's status as a star is a function of their innate ability, which is something that money cannot buy. That said, to the extent that a player with potential talent on the margin of being star quality can be identified, it might be possible to develop that player over a season and turn him into a star. However, I would argue that this is more a function of the coaching staff recognizing a player's potential and devoting more time and attention to the player, rather than the affect of any direct monetary expenditure. It is also unlikely that current season revenues are used to incetivize coaches to develop talent as coaching staff salaries are already established at the beginning of the season. Furthermore, to the extent that any financial incentive to develop talent exists, the coaching staff's incentive is likely forward-looking: developing talent in the hopes to make the team better and negotiate a higher wage in the future. The second reason why we should not be worried about reverse causality is that athletic program budgets are set in the fiscal year prior to the start of the football or basketball season. So even if a team is generating a lot of revenues in the current season, their operating budgets for that season will have already been set the year before. Hence, it is difficult to see how idiosyncratically high revenues in the current season could be directly used to influence player development in that season when the team's budget has been set the year before revenues were idiosyncratically high.

More concerning than reverse causality is the potential for omitted variables to bias the estimates of a star player's MRP. In the current context, it is likely that these omitted variables would come in one of two forms: either from selection bias causing the error term in Equation (2.1) to be correlated with the number of star players on the team (since we cannot observe all the factors influencing selection to teams in the recruiting process) or from excluding team-level variables that are potentially driving revenues. In either case, the omitted variable bias is likely to bias the MRP estimates upward as it is difficult to imagine variables that would be positively correlated with revenues and negatively correlated with the number of star players.

Although I attempt to control for the recruiting process using the variables described in Section 2.3, these variables are only rough proxies for a complicated two-sided decision process that involves both individual players' choice of team and a recruiter's choice of players. My data allows me to attempt to control for a player's choice of team based on the empirical evidence that exists on how recruits select schools. Although, the process for how recruiters choose players, and in particular, how that choice is related to athletic program revenues in not directly observable in my data. However, in order for a recruiter's choice of players to bias the estimates, it must be the case that recruiters have some skill in choosing star players that will generate revenues above those generated by the average player on the team and my data does allow me to look at this. I present evidence in Section 2.7 that suggests recruiters are not particularly good at choosing players that will generate significantly more revenues than the average player on the team ex-ante. This result might help to alleviate some concerns over omitted variables related to the recruiting process biasing the MRP estimates.

In terms of team-level variables, the most obvious and important omitted variables in the empirical specification that affect revenues are the number of games the team won and if the team went to a bowl game or the NCAA tournament in the current season. As previously discussed, since these variables are themselves outcomes of the number of star players on the team that season, including them in the regression results in bias from bad control variables. Therefore, estimates of a star player's MRP will be severely biased, which could potentially be larger than the omitted variable bias resulting from excluding them from the regression. In the following section, I re-run the regression specification in Equation (2.1) that includes contemporaneous wins and discuss how these estimates can be thought of as a lower-bound on the magnitude of a star player's MRP.[72] I also present results from several alternative empirical strategies that attempt to alleviate concerns over the bias introduced by potential omitted variables in Sections 2.6,2.7, and 2.8.

2.5 Results

2.5.1 Marginal Revenue Product of Football Stars

The results of the fixed effect estimation of Equation (2.1) for star football players are presented in Table 13.[73] Marginal revenue product estimates are reported for all six measures of star player. Recall that the All-American star measure includes all positions while the

[72]In unreported results, I also included indicators for bowl game and NCAA tournament appearances in the current season with contemporaneous wins. The results are essentially unchanged and actually increase the point estimates slightly.

[73]The estimates in this table and all other tables in Section 2.5 use the continuous measure of star players. Estimates using the discrete measure of star players are similar and reported in Table 41 in Appendix A.7.

other five measures consist solely of Quarterbacks, Running Backs, and Wide Receivers by construction. Huber-White standard errors are computed, clustering by team, to account for potential correlation in the error term within teams and are reported in parentheses. The MRP estimates for all six measures of star player are statistically significant at the 5% level or better. The within R-squared is around 77%, suggesting the included covariates (after partialling out the fixed effects) explain a sizable portion of the variation in revenues. Furthermore, the overall R-squared of around 97% suggests there is a lot of variation in revenues accounted for by the unobserved heterogeneity being controlled for by team fixed effects.

The first column in the table reports the estimation results using the All-American Team measure of star and reveals that the MRP of an All-American player is just over $1.2 million a year. In other words, having an additional All-American caliber football player on the team generates, on average, just over $1.2 million of additional revenue for the team. The regression results for Heisman finalists, reported in the second column, indicate that their MRP is just over $2 million a year on average, while the third column reports the MRP of a Heisman nominee is about $1.8 million a year on average. The fourth column reports the MRP of a football player who is among the top 10 in touchdowns or yards while the fifth column reports the MRP of a football player who is among the top 10 in touchdowns or yards or a top 10 Quarterback in terms of their PER. The last column reports the MRP of a football player who is a Running Back or Wide Receiver among the top 10 in touchdowns or yards or a top 10 Quarterback in terms of their PER. In all three cases, the estimated MRP of a star player according to these measures is just over $600,000 on average.

Individual Football Player Positions

A slight modification of Equation (2.1) allows me to estimate the MRP of star players in specific football positions as follows

$$y_{i,t} = \sum_{pos} \beta^{pos} Star_{i,t}^{pos} + X_{i,t}\gamma + \theta_i t + \delta_t + \delta_c + \delta_i + \epsilon_{i,t} \tag{2.2}$$

where $\sum_{pos} Star_{i,t}^{pos} = Star_{i,t}$ and $pos \in \{QB, RB, WR, TE, OL, K, P, DB, LB, DL\}$ for the All-American star measure while $pos \in \{QB, RB, WR\}$ for the other measures.[74] The MRPs of star players in each position (β^{pos}) are jointly estimated using fixed effects and the same controls $X_{it,}$ as in Equation (2.1). The results of this fixed effect estimation are reported in Table 14.

Estimates for the MRP of an All-American Quarterback are \$4.6 million a year while a Heisman nominated and Heisman finalist Quarterback are worth \$2.2 and \$3.5 million a year on average. It is worth noting that all 14 All-American Quarterbacks in the data were also Heisman finalists so the reason that All-American Quarterbacks are worth more than Heisman finalists might simply be because they are mechanically more rare in the data. Also, a Quarterback among the top 10 in touchdowns and yards is worth just over \$1 million a year on average. All-American Wide Receivers are worth \$2.9 million a year on average while the MRPs for the rest of the positions across star measures were not statistically different from zero.

It might be surprising that the MRP estimates for Running Backs are not statistically significant in Table 14. This might be due to the fact, as Wesseling (2014) observes, that Running Backs are being devalued in college football due to an increase in college teams

[74]The positions abbreviations indicate: Quarterback (QB), Running Back (RB), Wide Receivers (WR), Tight Ends (TE), Offensive Linemen (OL), Kickers (K), Punters (P), Defensive Backs (DB), Linebackers (LB), and Defensive Linemen (DL).

emphasizing dual-threat quarterbacks operating out of a spread offense. He also reports that there is a general sense that Running Backs are not emphasized as much in college football as they are in the NFL. Nevertheless, the lack of statistical significance for positions other than Quarterbacks and Wide Receivers does not mean that star players in other positions are not generating large revenues for their schools. It simply means that the econometric specification cannot detect the effect. One downside of the fixed effect regression is that including fixed effects (in this case, team, year and conference) can also remove "good" variation that would help to identify the true effect. It might be the case that there is just not enough variation in the revenues data after controlling for these fixed effects to pick up the true effect of a star Running Back or Offensive Lineman on revenues when trying to jointly estimate multiple parameters.

2.5.2 Marginal Revenue Product of Basketball Stars

The estimates of star basketball player MRP from a fixed effects estimation of Equation (2.1) are reported in Table 15 for all eight measures of star player.[75] As with the football regressions, Huber-White standard errors are computed, clustering by team, and reported in parentheses. The MRP estimates for all eight measures of star player are statistically significant at the 5% level or better, with the exception of players ranked among the Top 10 points scorers, which are only significant at the 10% level. The within R-squared is around 67%, suggesting that the covariates explain a large portion of the variation in program revenues while the overall R-squared of around 97% suggests that the unobserved team characteristics controlled for by the fixed effects explain a lot of the variation in revenues.

The first column in Table 15 reports that the MRP of players who were named the NCAA Tournament's most outstanding player of the year, or won the Naismith Award, or won

[75]Estimates using the discrete measure of star player are similar and reported in Table 42 in Appendix A.7.

the Wooden Award is just over \$1 million a year. That is, having an additional player on your basketball team that is good enough to be awarded one of these honors generates, on average, just over \$1 million of additional revenues for the team. The results in the second column for players voted to the All-American first team indicate their MRP is over $\$654,000$ on average with the MRP for All-Americans in the third column just over $\$345,000$. Turning to the NBA draft measures, the fourth column reports the MRP of a player drafted into the NBA is just over $\$200,000$ while the MRPs of top 5 and top 10 NBA draft picks (columns 5 and 6) are around $\$400,000$. The previous studies that use instrumental variables report MRP estimates of NBA drafted players of just over \$1 million. However, this nearly five-fold discrepancy might be a consequence of the use of weak instruments in previous studies as a low correlation between the instrument(s) and the endogenous variable can cause a large upward bias in the point estimates.[76] The last column reports that the MRP of a player who was among the top 10 or 20 point scorers in a season is just over $\$300,000$ a year on average.

Table 15 also reports the estimates for coach quality and NCAA tournament performance that are of interest. For instance, each additional career NCAA tournament appearance a coach has (up to and including the prior season) is worth around $\$53,000$ a year to their current team and highly significant across all eight specifications. The variable $NCAATourn_{t-1}$ indicates if the team appeared in the NCAA tournament last season while $Champ_{t-1}$ indicates if they won the tournament last season. The resulting estimates from Equation (2.1) are that a previous appearance in the NCAA tournament generates $\$160,000 - \$170,000$ in revenues while winning the tournament generates $\$1.8 - \$2$ million in revenues on average for the team.

[76]One can show that in the univariate case, $plim\hat{\beta}_{IV} = \beta + \frac{corr(z,u)}{corr(z,x)}\frac{\sigma(u)}{\sigma(x)}$ where z is the instrument for endogenous x and u is the error term in the regression.

2.5.3 Lower Bound Estimates

The empirical strategy presented above potentially overstates the marginal contribution to revenues from individual players for two reasons. First, while excluding contemporaneous team control variables avoids introducing a potentially large bias from including bad controls, it also means the estimates for star player MRP will be partially capturing any revenues generated by the rest of the team's performance that is not being controlled for otherwise. This is precisely the omitted variable bias that results from excluding contemporaneous wins, bowl game and NCAA Tournament appearances from the regression. Secondly, estimating an individual star player's MRP in a team sport is further complicated by the fact that the skills of individual players interact. Since we cannot perfectly separate team from player and cannot identify cross-complementarities among players, the star player's MRP will include some indirect contributions to revenues coming from other players making the star player better and vice-versa.

Although identifying player complementarities is extremely difficult, including contemporaneous wins into the regression is straightforward. Including contemporaneous wins might result in a reasonable "lower-bound" for the MRP estimates reported in the previous sections for two reasons. First, since wins are positively correlated with football program revenues, including them will reduce the upward omitted variable bias in the current MRP estimates. Second, if wins are explicitly controlled for, then any impact on revenues that star players have through channels *other* than a star's contribution to the team winning will be captured in the MRP estimates. It is reasonable to think that winning is one of the most, if not *the* most, important factor for teams to generate revenue. Likewise, if star players have any ability to generate revenues for their teams, a significant portion of this effect is likely to come through their ability to produce wins. Hence, any residual effect that star players have on revenue after controlling for wins can be thought of as a "lower-bound" on the magnitude of a star player's MRP. However, including contemporaneous wins into the regression comes with a large caveat. As previously discussed, since wins are themselves an outcome of the number of star players on the team, including contemporaneous wins in the regression is a bad control variable. Therefore, estimates of a star player's MRP will be severely biased. This means that finding no effect of star players on athletic program revenues does not tell us much and that we can only really analyze results where both the coefficients on wins *and* star players are significant.

With this caveat in mind, Tables 16 and 17 reports the results for football stars of the fixed effects estimation of Equations (2.1) and (2.2) with the single modification that contemporaneous wins are included. From the tables, we see that the MRP for All-Americans (all positions, Quarterbacks and Wide Receivers), Heisman finalists and Heisman nominees are statistically significant and, while lower than the baseline estimates in Tables 13 and 14, still rather large. This suggests that star players have a sizable impact on revenues in ways unrelated directly to their contribution to producing wins for the team. If we view the estimates in Tables 16 and 17 as reasonable lower bounds, then All-Americans are worth $\$926k - \$1.2$ million, All-American Quarterbacks are worth $\$4 - 4.6\$$ million, All-American Wide Receivers are worth $\$2.7 - 2.9\$$ million, Hesiman finalists are worth $\$1.5 - \$2.1$ million and Heisman nominees are worth $\$1.2 - \$1.8$ million. While these lower bound estimates are similar in economic magnitude to the baseline estimates that omit wins, it is also worth noting that the coefficient estimates across all six measures of star player in Tables 13 and 16 are not statistically different from each other.

The results for basketball stars when contemporaneous wins are included are reported in Table 18 with only All-American first team players statistically significant at the 5% level. The MRP estimates for award winners, drafted players, top 10 draft picks and top 20 points scorers are all statistically significant at the 10% level. As with football, the MRP estimates including wins are lower than the baseline estimates in Table 15 but still quite large, suggesting that star basketball players also influence revenues in ways unrelated to their ability to produce wins. Taking these estimates as lower bounds, we see that award winners are worth $\$967k - \$1.1$ million, All-American first team players are worth $\$562k - 655k$, drafted players are worth $\$165k - \$204k$, top 10 draft picks are worth $\$314k - \$403k$ and top 20 points scorers are worth $\$261k - \$320k$. These lower bound estimates are very similar in magnitude to the baseline estimates and all eight star player measures in Tables 15 and 18 are not statistically different from each other.

In unreported results, I included indicators for bowl game and NCAA Tournament appearances for the current season along with contemporaneous wins. The results are essentially unchanged from those in Tables 16 and 18 and in fact, produce slightly higher MRP estimates for both football and basketball stars than when only including wins.[77] If we believe that a large portion of any potential omitted variables bias is coming through the omission of contemporaneous wins, it is somewhat reassuring that the lower-bound estimates are not drastically different in magnitude or statistically different than the baseline estimates. However, even though I have argued that including contemporaneous wins might give us a reasonable lower-bound on the MRP estimates, it is important to note that these estimates might still be biased upward if any omitted variables remains. While including wins might take care of a large portion of the omitted variables bias, there is still potential for omitted variables bias in these lower-bound estimates. As discussed above, one potential source of this bias might be my inability to perfectly control for the recruiting process with the observable measures available in my data.

2.5.4 Discussion

Huma and Staurowsky (2012) report that the average full athletic scholarship is worth approximately $\$23,204$. While this does not capture the true marginal cost of a star college

[77]These results are available upon request.

athlete, the difference between the marginal revenue products in Tables 13 and 15 and the value of a full athletic scholarship gives a decent approximation of the economic rents being captured by universities under the NCAA rules restricting payment.[78] Furthermore, comparing the size of these rents with the average salaries for NFL and NBA players who are able to sell their services in a more competitive labor market gives a sense of the economic significance of the rents being captured.

The average salary for an NFL player in 2014 was $\$1,673,277$.[79] This figure is roughly similar in magnitude to the MRP estimates for All-American players ($\$926k - \$1.2$ million), which includes players in all positions that are likely to be good enough to be picked up by a professional football team. Furthermore, the average salary in 2014 for NFL Quarterbacks, Running Backs, and Wide Receivers collectively ($\$2,058,698$) was very similar to the MRP estimates for Heisman finalists ($\$1.5 - \$2.1$ million) and Heisman nominated players ($\$1.2 - \$1.8$ million). Turning to individual positions, average salaries for NFL Quarterbacks ($\$4,183,581$) in 2014 were in the range of the MRP estimates for All-American Quarterbacks ($\$4 - \$4.6$ million) while the average salaries for NFL Wide Receivers ($\$1,743,160$) was lower than the MRP estimates for All-American Wide Receivers ($\$2.7 - \$2.9$ million).[80] These results indicate that the rents of star college football players being captured by universities are economically significant considering they are similar, on average, to the wage these star players might earn if they were allowed to be paid according to their marginal productivity.

[78] See Getz and Siegfried (2012) for a discussion of the difficulty associated with accounting for revenues and expenses in academic institutions. Also, the true marginal cost of fielding a star player might be much larger than the cost of athletic scholarships. For instance, if star players require more attention or are more difficult to manage than average player on the team, this marginal cost of an additional star player will not be captured in the cost of an athletic scholarship.

[79] The data for 2014 NFL player salaries were collected from http://www.sportscity.com/nfl/salaries/ and the nominal 2014 values were deflated to real 2012 USD using the consumer price index for all urban consumers from the U.S. Bureau of Labor and Statistics.

[80] The data for 2014 NFL player salaries by position were collected from http://www.sportscity.com/nfl/salaries/ and the nominal 2014 values were deflated to real 2012 USD using the consumer price index for all urban consumers from the U.S. Bureau of Labor and Statistics. Sports Illustrated (2013) reports average (nominal) 2014 salaries of simlar magnitudes for Quarterbacks ($\$3,840,017$) and Wide Receivers ($\$1,803,338$).

The average salary for an NBA player in 2014 was $\$4,390,800$.[81] Hence, the average NBA salary is just over four times the magnitude of the largest MRP estimates in Table 15 and roughly 21 times the size of the MRP estimate for college players drafted into the NBA. The size of this latter discrepancy might be surprising given the fact that the MRP estimate is for college players that were drafted to play in the NBA. However, I would only expect the average salary for NBA players and the average MRP of college players drafted into the NBA to be similar if consumers of sports entertainment view college and professional basketball as reasonably close substitutes and/or if the markets for college and professional basketball are similar. There are several reasons why this might not be the case. For instance, there are far more regular season games and far fewer teams in the NBA compared to the NCAA.[82] Also, the average NBA team has much more lucrative televisions contracts and the NBA is consumed internationally, whereas there is virtually no demand for NCAA basketball outside of the United States. All these factors allow NBA teams to generate much larger revenues than NCAA teams, which is likely why there are large discrepancies in the relative values "paid" to their inputs to production (players).[83]

Even though the player generated rents being captured by institutions are large, reasonable counter-arguments against the exploitative nature of this arrangement could be made. For instance, playing football or basketball in college gives players time to grow and mature both physically and mentally; it also allows them to learn the technical aspects of the game and improve their skills. These features of playing for a college team prepare athletes to

[81] The data for 2014 NBA player salaries were collected from http://www.sportscity.com/nba/salaries/ and include all teams excpet the New Orleans Hornets and the Portland Trailblazers, for which these data were not available. The nominal 2014 average salary was $\$4,527,385$, however for comparison with the estimates, this nominal value has been deflated to real 2012 USD using the consumer price index for all urban consumers from the U.S. Bureau of Labor and Statistics.

[82] There are 32 professional NBA teams that played 82 regular season games in the NBA 2013–2014 regular season while there are 351 Division 1 men's college basketball teams that typically play 30 regular season games.

[83] Of course, in the case of the NBA the amount paid is the player's actual salary, while the maximum amount paid to college players would be (approximately) their MRP if they were allowed to sell their labor.

enter into a potentially lucrative labor market as professional athletes. Furthermore, their commitment to a college team is not a binding contract for the entire four years of an undergraduate education as players that have developed their skills enough have the option of leaving college early to pursue a professional career. One could view these forgone rents as an implicit "tax" or licensing fee that athletes pay for access to the potentially lucrative professional sports labor market. However, Brown (2012) shows that for the 2004–2005 season, only around one-third of college football players in his sample will earn NFL incomes large enough to offset the rents forgone by these players.

There are other reasons why we might not want to compensate college athletes beyond scholarships of in-kind transfers to cover basic costs and tuition. For instance, in my data, only about 9% of Division 1 FBS college football players are drafted into the NFL while only about 1% of Division 1 men's college basketball players are drafted into the NBA. Keep in mind, these are just players that are drafted and does not account for players that were drafted, then subsequently cut from their NFL or NBA team's full roster. Given that the chances of making it into professional football or basketball's labor market from college are so small, we might worry about students' unrealistic expectations distorting their human capital allocation decision. That is, a student's unrealistic aspirations might cause them to tradeoff athletics over academics when deciding on what college to attend or to allocate more time to athletics than academics once in college. Paying college athletes might only serve to further encourage this distorted allocation of human capital as the additional financial incentive might persuade a student on the margin to make the above tradeoff.

Overall, the purpose of this empirical analysis is to focus on the size of the rents being captured by institutions to help inform the larger debate as to if this practice is exploitative. Regardless of one's position on the fairness of the arrangement, the analysis does seem to indicate that rents generated by the very best college football and basketball players being captured by NCAA member institution are both economically and statistically significant.

2.6 Robustness

Given the panel nature of the data, there are several econometric methods that could have been used to control for unobserved team characteristics, fixed effects being only one. For example, a random effects model could have been used to estimate Equation (2.1). Although the additional assumption needed that the time-constant unobserved team heterogeneity is uncorrelated with the number of star players on a team is very unlikely to hold, I estimated the random effects model and report the results of a Hausman Test. For the models with each of the six different measures of star football players and eight measures of star basketball players, the Hausman Test strongly rejected the null hypothesis that the coefficients estimated by the random effects estimator are equal to those estimated using fixed effects ($Prob > \chi^2 = 0.0000$ in all cases).[84] Hence, the fixed effect specification appears to be the appropriate one. In what follows, I present the results of a first difference estimation of Equation (2.1) as well as a lag revenue model and compare these results with the MRP estimates for star players in Ta bles 13 and 15. For basketball, I present an additional robustness check and report fixed effects estimates for the subsample of Division 1 men's basketball teams that also have Division 1 FBS football programs.

2.6.1 First Difference Model

An alternative way to account for unobserved team characteristics in Equation (2.1) is to transform it using first differences

$$\Delta y_{i,t} = \eta \Delta Star_{i,t} + \Delta X_{i,t}\gamma + \theta_i + \Delta\delta_t + \Delta\delta_c + \Delta\epsilon_{i,t} \tag{2.3}$$

[84]The value of the χ^2 test statistic was at or above 40 for all six football star measure regressions and 61 for all eight basketball star measure regressions.

and estimate the first difference estimator $\hat{\eta}$. The first difference model requires a weaker exogeneity assumption than the fixed effects estimator in that $\epsilon_{i,s}$ only has to be uncorrelated with the covariates for $s = t, t-1$. If there is any feedback from $\epsilon_{i,t}$ to $Star_{i,t}$ that goes farther back than one period, the first difference estimator will be consistent whereas the fixed effect estimator will not. Given this, I can compare the fixed effect and first-difference estimators to see if they are similar. If the differences in these two estimates cannot be attributed to sampling error, we should worry about the validity of the strict exogeneity assumption in the fixed effect estimation.

For football, the first difference estimation of Equation (2.3) is reported in Table 19. Comparing the first difference estimates with the fixed effect estimates in Table 13 we see that the estimates are fairly close to each other, particularly for star measures 1 and 3-6. It is reasonable to conclude that these differences are likely attributable to sampling error since the first-difference estimator uses 10% less observations than the fixed effect estimator and these first-difference estimates are not statistically different from the fixed effect estimates. Furthermore, recall that there are only 46 Heisman finalists in the full sample, which is by far the smallest category. Therefore, this measure is likely to be the most sensitive to sample size as it becomes increasingly difficult to detect any true effect of star players the fewer number of stars we observe. This may be why the estimates for Heisman finalists are not estimated as precisely in the first difference regression and the disparity between them and the fixed effect estimates are the largest. In fact, the estimates that are the closest to the fixed effects estimates (4-6) are the star player measures with the largest number of star players. For basketball, the first difference estimation of Equation (2.3) is reported in Table 20. Comparing the first difference estimates to the fixed effect estimates in Table 15 we see that the estimates are very close to each other, both in terms of size and statistical significance with the first-difference and fixed effects estimates not statistically different from each other. Therefore, as is the case with football, it seems reasonable to conclude that any differences between first-difference and fixed effects estimates are likely attributable to sampling error.

Ultimately, the fixed effects model is my preferred specification for three reasons. First, I prefer to estimate the star player's MRP from a larger sample of observations and 10% of the observations are lost using the first-difference estimator. Second, if the exogeneity assumption holds contemporaneously and for one-period lag—which seems plausible after controlling for one and two year lags of $Star_{i,t}$, $Wins_{i,t}$, and the other controls—then the fixed effects estimator might be better because its inconsistency shrinks to zero at rate $1/T$, which is not the case for the first difference estimator. Lastly, under the null hypothesis that the model in Equation (2.1) is correctly specified, the fixed effect and first-difference estimators will differ only because of sampling error if $T \geq 3$. Then because the first-difference estimates are relatively close to the fixed effect estimates and statistically indistinguishable, I take this as evidence supporting the validity of the strict exogeneity assumption of the fixed effect model. However, this does not provide a formal test ruling out the potential for omitted variables because it might still be the case that omitted variables are biasing the fixed effects and first-difference estimates in the same way. Although, in order for this to be the case, the omitted variables that we should be worried about are those that are correlated with the number of star players in t and $t-1$ due to the weaker exogeneity assumption of the first-difference estimator. This information is useful because it means that the omitted variables that are likely to cause the most concern are those that are endogenous with at most a one-period lag.

This could partially alleviate concerns discussed earlier regarding omitted variables associated with a team's recruiting process. Since the recruiting process takes place more than one year before these players are designated as stars, the results discussed in this section might imply that team fixed effects and the included controls for recruiting effort are largely sufficient to minimize concerns over omitted variables related to a team's recruiting effort.

As previously discussed, the other source of omitted variables are team-level variables that are potentially driving revenues with contemporaneous wins being an obvious one. While I do control for numerous macro-level and team-level variables that could influence a team's revenues over $t-1$ and $t-2$, I can never entirely rule out omitted variables bias in the fixed effect framework of Section 2.4. That the difference between the fixed effects and first-difference estimators is likely due to sampling error, coupled with the fact that including contemporaneous wins does not drastically change the fixed effect MRP estimates, seems to provide reasonable evidence that the estimates are not grossly biased due to omitted variables.

2.6.2 Lag Revenues Model

One could argue that past football and basketball program revenues influence future revenues and that omitting lagged values of revenues in Equation (2.1) is a potential source of model misspecification or omitted variables bias. If so, a model for football or basketball program revenues might look like this

$$y_{i,t} = \beta_1 Star_{i,t} + \beta_2 y_{i,t-1} + \beta_3 y_{i,t-2} + X_{i,t}\gamma + \theta_i t + \delta_t + \epsilon_{i,t} \tag{2.4}$$

where $X_{i,t}$ contains the same control variables as before. The main differences between this model and Equation (2.1) is the inclusion of one and two years of lagged football or basketball program revenues and the exclusion of conference and team fixed effects. It is important to exclude these fixed effects because, as Nickell (1981) points out, OLS estimates of a dynamic panel model that includes fixed effects to control for unobserved heterogeneity can be severely biased due to correlation between the fixed effects and the lag dependent variable built into the specification.[85]

[85] Judson and Owen (1999) further show that this bias is inversely related to T and that the bias is problematic even with T as large as 30.

I estimate the model in (2.4) using OLS and present the results in Tables 21 and 22. The coefficient on lagged football program revenues is highly significant for all six measures of star player, indicating that an additional dollar of football program revenues in the previous year is associated with around 63 cents of additional revenue in the current year. Likewise the coefficient on lagged basketball program revenues is highly significant for all eight measures of star player, indicating that an additional dollar of basketball program revenues in the previous year are associated with around 44 cents of additional revenue in the current year.

For football, the robustness of the fixed effects results are encouraged by the fact that the estimates of star player MRP for measures (1,4-6) under the lag model are close and statistically indistinguishable to the fixed effects estimates in Table 13. However, the estimates for Heisman finalists and Heisman nominees under the lag model are quite different and not statistically significant (although still statistically indistinguishable from their fixed effect estimates). This is likely due to the fact that I am unable to control for athletic conference fixed effects in the lag model and a few conferences produce the majority of Heisman nominees and finalists. For instance, out of the thirteen conferences in the data from 2003-2012, four of them produced just over 64% of Heisman nominees and almost 82% of Heisman finalists.[86] A similar feature of the data exists for All-Americans with the same four conferences producing almost 77% of All-American players.[87]. Similarly, for basketball the robustness of the fixed effects estimates are supported by the fact that the estimates for all eight measures of star player MRP under the lag model are very close and not statistically different from the fixed effects estimates in Table 15.

Although the lag model of Equation (2.4) might seem appealing, it is difficult to come up with an *economic* reason for why past football and basketball program revenues would

[86] Those conferences were The Big 12, The Big Ten, The PAC-10 and the SEC.

[87] By contrast, these same four conferences only produce 43% of the star players measures (3-6).

influence current football program revenues in ways not being controlled for in the fixed effect regressions. However, it is easy to come up with examples of unobserved team characteristics that might be correlated with the number of star players on a team that also influence football and basketball program revenues. For instance, a team's geographic location, athletic legacy, and "sporting culture" are likely correlated with the number of star players on those teams *and* affect their ability to generate revenues. Likewise, because some athletic conferences generate both more revenues *and* star players, it is important to be able to control for both team and conference fixed effects, which cannot be done under the lag model specification. Hence, the fixed effect model is still preferred while the lag model results provide evidence that the fixed effect estimates are fairly robust to this alternative model specification.

2.6.3 Basketball Programs With Division 1 FBS Football Programs

The above analysis estimating star basketball player MRP includes 282 of the 351 men's Division 1 basketball teams. However, many of these teams come from small schools whose basketball programs probably do not generate large revenues. One might argue that it makes more sense to focus on the Division 1 basketball teams of schools that also field a Division 1 FBS football program. The rational behind this idea is that using a sample where the majority of programs are from smaller schools might result in smaller estimates of a player's MRP because basketball programs at schools that also have an FBS football program tend to be big-name programs. These big-name athletics programs tend to be housed at larger, more recognized universities and are able to generate higher revenues. While the school fixed effects and other control variables included in the analysis should account for this, it is useful as a robustness check to look at the subsample containing only these big-name schools to see if the MRP estimates change significantly.

Table 23 reports summary statistics for 119 Division 1 men's basketball teams whose institutions also fielded Division 1 FBS football teams over the sample period 2003–2012. The differences between this subsample and the full sample statistics in Table 9 are immediately obvious with average basketball program revenues almost twice as high and the average undergraduate population larger by nearly 7,000 students. This subsample of teams also tends to perform better, winning two more games on average, going to the NCAA tournament more often and performing better in the tournament. The fixed effect estimates from Equation (2.1) of the MRP for star players on Division 1 basketball teams that also field a FBS football team are reported in 24. Comparing these estimates with those from the full sample of teams in Table 15 reveals very similar results both in terms of magnitude and statistical significance.

It is worth noting that the majority of star players in the data come from one of the big-name teams in the subsample. For example, 60% of players drafted into the NBA come from one of these teams along with 77% top 5 and 66% top 10 draft picks. Likewise, 89% of Award Winners, 78% of All-American first team members and 76% of All-Americans come from basketball teams whose institutions also have an FBS football team. Therefore, it is not too surprising that the MPR estimates between the subsample and the full sample are quite close. Nevertheless, it is reassuring that the MRP estimates do not change much when considering this subsample of the data.

2.7 Ex-Ante Star Player Measures

The empirical analysis so far has focused on definitions of star players that rely on ex-post measures of player performance. One advantage of my data is that it allows me to define ex-ante measures that designate a player as a star based on how players are expected to perform in college before signing with a college team. These measures are based on the Yahoo! Sports Rivals.com rankings, which aggregates information from professional recruiting analysts, high school, and college coaches about high school football and basketball players' expected performance at the collegiate level. To the extent that the Rivals.com rankings are a good proxy for the information set of college recruiters looking to recruit top high school talent, estimating the MRP of ex-ante star college players is interesting for two reasons.

First, since the previous analysis of ex-post star players seems to indicate that they generate significant revenues for their teams, it is interesting to see if college recruiters are able to identify players beforehand that will generate significant revenues for the team. This ability (or inability) has important implications for how we might compensate college athletes if they were to be compensated beyond the current arrangement. Second, the ability of college recruiters to identify players ex-ante that will generate significantly more revenues than the average player for the school is important for questions concerning omitted variables related to the recruiting process biasing the MRP estimates of ex-post stars. That is, if recruiters can identify talented players ex-ante that will generate significantly more revenues than the average player for the school and since these players are likely to become ex-post stars players, then the MRP estimates will be biased as unobserved variables related to the recruiting process will be correlated with both revenues and the number of ex-post star players on a team.

Recall the six measures of ex-ante football star and the single measure of ex-ante basketball star in Table 12 discussed in Section 2.3. Ideally, these ex-ante measures would result in the same frequency of star players as the ex-post measures to facilitate comparison of the estimates. The frequencies in Table 12 compared with those in Tables 10 and 11 reveal that the ex-ante measures are slightly more permissive, however, the most restrictive definitions of ex-ante star player were used given how Rivals.com ranks football and basketball recruits. Equation (2.1) is used to estimate the MRP of ex-ante star players using fixed effects, where the only modification from the empirical analysis in Section 2.4 is that the regression is run over the sample $2005-2012$ and $Stars_{i,t}$ are defined to be one of the ex-ante star player measures in Table 12.

2.7.1 Results

The estimates for ex-ante star football and basketball player MRPs from a fixed effects estimation of Equation (2.1) are reported in Tables 25 and 26. Huber-White standard errors are computed, clustering by team, and reported in parentheses. For football, the MRP estimates for all ex-ante measures of star player are not statistically significant while the MRP estimates for ex-ante basketball stars are only statistically significant at the 10% level. It is worth reiterating that the MRP estimates from Equation (2.1) using fixed effects measure the marginal revenue generated by a star player on a team *relative* to the average player on that team and the ex-ante estimates in Tables 25 and 26 have the same interpretation. Therefore, these results suggest that there is no statistical evidence that recruiters are able to identify players who will generate more revenues than the average player on the team.

To be clear, these results *do not* say that recruiters cannot identify revenue generating talent ex-ante. For example, suppose that the average basketball player at Duke generates $\$300,000$ in revenues while the average player at the University of Utah only generates $\$50,000$. The results imply that even if Duke's recruiters can sign players that will generate higher revenues, neither Duke's nor Utah's recruiters can identify star players ex-ante that will generate more revenues than what the average player on each team would generate. Keep in mind, this conclusion relies on the assumption that the information aggregated by Rivals.com is a reasonable approximation of the information set that recruiters have when recruiting players to their teams. One implication of these results is that if the NCAA were to allow athletes to be paid for their athletic ability, then universities should prefer a compensation scheme that puts less weight on up-front compensation and more weight on a performance bonus, paid after a player's ability to generate revenues is revealed.

Expected and Unexpected Star Players

From the previous section, there appears to be little evidence in football and weak evidence in basketball that college recruiters can identify players ex-ante that will generate significantly more revenues than the average player for their college teams. While this might help assuage concerns of omitted variable bias associated with recruiting effort, this result holds on average and does not rule out the possibility that certain recruiters might be able to identify players ex-ante that will generate more revenues than the average player on their team. Furthermore, if players that were expected to be good ex-ante turn out to be star players ex-post and if these players generate significantly more revenues than the average player relative to unexpected stars, we might still worry about omitted variables bias in recruiting. Therefore, it is useful to decompose the ex-post measures of star player into their "expected" and "unexpected" components.

For football, I define "expected" stars to be ex-post star players that were also designated as a Top Rivals star ex-ante. These are players that college recruiters expected to be star college players that turned out to be stars according to the relevant ex-post measure. I choose to use only the Top Rivals ranking for football because this is the ex-ante measure that is most analogous to the ex-post measures in Table 10, both in terms of the criteria defining star players and in the relative frequency of these players in the data. Then "unexpected" stars are just the ex-post star players that were *not* designated as Top Rivals stars ex-ante. These are players that college recruiters did not expect to be star college players that turned out to be stars ex-post. Likewise, for basketball, I define expected stars to be ex-post star players that were also designated as a Rivals.com 5 Star recruit with unexpected stars being ex-post star players that were not designated as a Rivlas.com 5 Star recruit.

Equation (2.1) is used to estimate the MRP of expected and unexpected star players using fixed effects, where the only modification from the empirical analysis in Section 2.4 is that the regression is run over the sample $2005-2012$ and $Stars_{i,t}$ is decomposed into its mutually exclusive components $ExpectedStars_{i,t}$ and $UnexpectedStars_{i,t}$ where $Stars_{i,t} = ExpectedStars_{i,t} + UnexpectedStars_{i,t}$. Table 27 reports the MRP for expected and unexpected football stars with Huber-White standard errors, clustered by team, reported in parentheses. Immediately from the table it is apparent that the MRPs of unexpected stars are statistically significant for all measures of star player except for Heisman finalists. The fact that the MRP of expected stars are not statistically significant for all but All-American and Heisman finalists might give one pause. However, this is likely due to the fact that there are far fewer expected than unexpected stars across all measures and there might just not be enough power to identify the effect for expected stars when jointly estimating the two coefficients. The results for basketball are reported in 28 with the MRP of unexpected stars being statistically significant at the 5% level for All-American first team and drafted players with top draft picks and top 20 points scorers significant at the 10% level. As with football, the fact that the MRP of expected stars are not statically significant for many of the star measures is likely due to lack of power coming from few observations.

The fact that unexpected football and basketball stars tend to significantly impact revenues helps mitigate concerns that skilled players who turn into stars are being selected by top recruiters ex-ante and this selection is biasing the MRP estimates. Furthermore, F-stats and p-vales reported at the bottom of Tables 27 and 28 reveal that we cannot reject the null hypothesis that the coefficient estimates for expected and unexpected stars are statistically different from each other for almost all star measures.[88] Simply put, it appears there is

[88]The lone exception is the MRP estimates for expected and unexpected basketball players that were in the top 20 point scorers. Looking at the individual data reveals that there are two well known NBA basketball players that were Rivals.com 5 star rated *and* top 20 points scorers in college: James Harden and Chris Humphries. Since there are only nineteen expected stars in this category this estimate is likely sensitive to

no statistical difference between a star's impact on team revenues who was expected to be a star and one who was a surprise. Although concerns over omitted variables biasing the MRP estimates through recruiting's selection process cannot completely be ruled out, these results are encouraging for the MRP estimates of ex-post stars.

2.8 Alternative Empirical Strategies

Although the empirical strategy presented thus far attempts to account for omitted variables as well as possible, we can never be completely sure that the MRP estimates presented above have a causal interpretation. When thinking about methods for inferring causality, one immediately looks for sources of exogenous variation in the number of star players unrelated to team revenues. In the current context, it is natural to think about using injuries and suspensions as potential sources of exogenous variation as these are plausibly random events that affect in the number of star players in a given season.

While injuries and suspensions are not identified directly in my data, I can use the percentage of games played by each player in my individual-level data to narrow down the search for injuries and suspensions. To this end, for each measure of ex-post star football and basketball player, I collected a list of players that were designated as stars in year t and played no more than half of their team's games in year $t+1$. Then for each of these players, I manually searched their player biographies on the websites of their respective athletic programs to determine if the low games-played percentage was due to injury or suspension. Having identified star players that played no more than 50% of games in the

outliers. That is, the fact that expected stars in this category are statistically different than unexpected stars and much larger than the composite estimate in Table 15 might really be due to the "Harden" and "Humphries" effect if they happen to be extremely valuable to their college teams realative to the average unexpected star in that category. The reason we do not see this same pattern in the top 10 points scorers measure is likely beacuse these two players are not included in that measure, which just suggests that top points scorer might just be a fairly noisy measure of quality as it pertains to players ability to generate revenues.

subsequent season due to injury or suspension, I then determined which of these injuries or suspensions were "season ending." I define a season ending injury or suspension as being one that causes a player to miss at least the last-half of the season and rule out players that were "plagued by injury." For instance, I do not count a player who was injured for part of the season, then came back from injury to play the remaining games, even if they ended up playing only 40% of games that season. The reason I do this is that I want the injury or suspension to cleanly end a star player's contribution to team output. For example, I do not want to count players that were injured, then came back from injury to help their team into the NCAA tournament or a bowl game as this will muddy any identification strategy using injured players to estimate a star player's effect on revenues.

Table 29 reports the number of injured star players I was able to identify in the data. As seen in the table, there are shockingly few season ending injuries.[89] This low number of identified injuries does not appear to be due to missing data. For instance, checking my team and individual-level data reveals that very few players and no teams are missing the number of games played, which would cause my initial screening to potentially miss a number of injuries. Furthermore, in manually searching for the biographies of the screened list of players, I did not encounter anyone that I could not find a biography for, which makes sense given these are all star players. The likely explanation for the low number of identified injuries is simply that season ending injuries are not extremely common events, which is compounded by the fact that stars players are very rare in the first place. Despite the limited number of injuries and suspensions in the data, I use this source of exogenous variation to supplement my previous estimates of star player MRP using instrumental variables and a generalized difference-in-difference approach.

[89] Including players who had seasons "plagued by injury" does not add a significant number of injured stars to the data. Therefore, I continue with season ending injuries and suspensions because these potentially provide cleaner identification of the effect of interest.

2.8.1 Instrumental Variables

An instrumental variables framework appears to be the method of choice in dealing with potential exogeneity in the literature that attempts to estimate the MRP of star college athletes. However, as already discussed, there are issues with the validity of the instruments used in the literature, particularly with satisfying the exclusion restriction and the problem with weak instruments. Although there is no guarantee that using injuries will provide a better instrument, I use the number of injured star players last season as an instrument for the number of star players in the current season.[90] This instrument should satisfy the exclusion restriction required for the instrumental variables estimator as it is plausible to assume the number of injured stars last year should only affect the team's current revenues through its effect on the number of star players in in the current year.

I use this instrument to exactly identify the number of star players ($Star_{i,t}$) in an instrumental variables estimation of star player MRP in Equation (2.1). All the control variables used in the fixed effects analysis mentioned in Section 2.4 are included as well as team, conference and year fixed effects. The instrumental variable regression results for football are reported in Table 30. Immediately we see that none of the estimates are statistically significant with the exception of the All-American estimates, which are significant at the 10% level. If one believes that the instrumental variables estimates captures the "true effect" in a way that the OLS fixed effects estimates do not, then one might be tempted to conclude that star football players do *not* generate revenues for their teams. However, I would argue that these results should not be taken very seriously for two reasons.

First, the instrument is, for the most part, very weak since almost every F-statistic from the first stage regressions (reported at the bottom of the table) are less than ten.[91] Further-

[90]In the remainder of the paper, when I refer to injuries, I am referring to injuries and suspensions.
[91]The full first stage results are reported in Table 55 of Appendix A.7.

more, even though the F-statistics for the instrument in the case of All-Americans appears quite strong, in this context, it might be misleading. The reason is that since there are so few injured stars, the instrument is going to contain mostly zeros. Likewise, there are very few star players so the variable $Stars_{i,t}$ will also contain mostly zeros. Therefore, the instrument might be "highly predictive" overall because it correctly "predicts" when there are no star players even though it might almost never predict the number of star players for non-zero values of injured players and star players.

Second, since any omitted variables are likely to be positively correlated with both the number of star players *and* a team's revenues, we would expect the instrumental variables estimates to be *lower* than the OLS estimates reported in Table 13. Even if we think that the instrument is valid for All-Americans, the MRP estimate using instrumental variables is *larger* than the MRP estimate for All-Americans using OLS. For the instrumental variable estimator $\hat{\beta}_{IV}$, one can show that in the univariate case $plim\hat{\beta}_{IV} = \beta + \frac{corr(z,u)}{corr(z,x)}\frac{\sigma(u)}{\sigma(x)}$ where z is the instrument for endogenous x and u is the error term in the regression. Recall that there are very few star players, which means that $Stars_{i,t}$ contains mostly zeros. Hence, there is not a lot of variation in the endogenous variable, which will bias $\hat{\beta}_{IV}$ up as $\sigma(x)$ is very small.

For completeness, the instrumental variable results for basketball are reported in Table 31 for the only two measures of star player that had any injuries.[92] Recall there was only one injured star player in the top 10 and 20 points scorers, and in the former case, the instrument happens to be collinear with some of the control variables in the regression, which is why there is no estimate for this measure. The instrumental variable estimates for basketball should not be taken seriously for the same reasons that the football estimates are suspect. Overall, the instrumental variables approach does not seem feasible given the

[92]The full first stage results for basketball are also reported in Table 57 of Appendix A.7.

limited number of injuries and suspensions in the data. It is likely that we would need to observe many more seasons of player data to get enough star players and injuries or suspensions if we are to reliably identify the true effect when using them as instrumental variables.

2.8.2 Difference In Difference

Although the instrumental variables approach was not entirely feasible, I can use the loss of a star player due to injury or suspension to estimate star player MRP in a generalized Differences-In-Differences framework for multiple events. Consider the following model for a *single event*

$$y_{i,t} = \beta(d_i \times p_t) + \alpha_i + \delta_t + \epsilon_{i,t}$$

where $y_{i,t}$ are revenues for team i in year t, d_i is an indicator for team i being treated in that particular event and p_t is an indicator for treatment having occurred by period t. Also included are team (α_i) and year (δ_t) fixed effects. Losing a star player due to injury from one season to the next is *one* event and this event can affect different teams at different times. Following **?** I create a sample for each event and stack these samples, identifying each separate season (two adjacent years) as a cohort. This stacked data can then be represented by the following model

$$y_{ict} = \beta d_{ict} + \alpha_{ic} + \delta_{tc} + \epsilon_{ict} \tag{2.5}$$

where c denotes the cohort and d_{ict}, the interaction between treatment and the post-treatment period, with β the difference-in-difference estimator. The fixed effect α_{ic} controls for the treatment within each cohort while δ_{tc} controls for post-treatment within each cohort.

For the difference-in-difference estimator β to have a causal interpretation, the treatment must be random, which seems plausible in this context. However, the additional parallel trends assumption needed for identification is that absent treatment, the change in team revenues for a team that loses a star due to injury would not have been different than the change in revenues for the teams that do not lose a star due to injury. The advantage of the multiple events framework is that it allows different teams to be treated at different points in time and the more events we have, the harder it is to argue that a particular set of treated teams is driving the result. That is, we would need to come up with a compelling story as to why the parallel trends assumption is violated for each unique event.

I will define a team as being treated in two ways. First, if the team had exactly one star player in year t, lost that player due to injury in $t + 1$ and had zero star players in year $t + 1$. The second definition is identical to the first, except the treated team can have zero or one star players in year $t + 1$, that is, I allow the star to be replaced by exactly one other star player. The control group of teams are those that had exactly one star player in year t, did not loose a star player due to injury, and had exactly one star player in year $t + 1$. This definition of treatment and control groups is very restrictive. The consequence of this restriction is that only three measures of star football players (TDYds, PERTDsYDs, and TopPER) and two measures of star basketball players (Top 10 and 20 points scorers) have any treated teams in the sample. Furthermore, the number of treatment events is quite small, which attenuates some of the strengths of this multiple event approach. However, even though these definitions are restrictive, they help the identification strategy in two way. First, the parallel trends assumption is more likely to hold as I have defined treatment and control teams. The reason is that, as currently defined, the difference-in-difference regression will only be comparing teams that had exactly one star player in a season. Teams that have a lot of star players are likely much different than teams that have very few star players, particularly in terms of revenues. Hence, it is more plausible that the trends in revenues before and after treatment between the treated and untreated teams are similar in making this restriction since I will not be comparing teams that have a lot of star players with those that have few. Second, these definitions of treatment and control provide the cleanest possible identification for the impact on revenues caused by the loss of a star player and will not be confounded by the team having a lot of other star players, gaining star players, or loosing multiple star players in a year.

Gaining Versus Losing a Star Player

Since the differences-in-differences estimator is identified in a completely different way than the OLS estimates using fixed effects, it might be useful to compare the estimates of a star player's MRP under each method. However, the two methods produce MRP estimates with slightly different interpretations. The differences-in-differences method will estimate the team revenue *lost* when a team loses a star player due to injury while the OLS method using fixed effects or first-differences assumes gaining and losing a star player is symmetric in terms of its effect on revenues. Therefore, if we want to compare the estimates from using these two methods, it will be useful to know if there is any difference in the impact on team revenues between gaining and losing a star player under the OLS framework. To answer this, consider the following model

$$\Delta y_{i,t} = \eta_1 \Delta Star_{i,t} \times \mathbf{1}_{\{\Delta \geq 0\}} + \eta_2 \left|\Delta Star_{i,t}\right| \times \mathbf{1}_{\{\Delta < 0\}} + \Delta X_{i,t}\gamma + \theta_i + \Delta\delta_t + \Delta\delta_c + \Delta\epsilon_{i,t} \tag{2.6}$$

which is identical to the first-difference model of Equation (2.3) with the exception that the change in the number of star players ($\Delta Star_{i,t}$) is decomposed into its non-negative and negative domains with an indicator function.[93]

The estimation results of Equation (2.6) for football are reported in Table 32 along with

[93] Note that the indicator function splits the number of star players into its non-negative and negative domains using the discrete measure of star player rather than the continuous measure. Also, the absolute value is taken over the negative domain to help improve the interpretation of the coefficient estimates in Tables 32 and 33.

F-statistics for the null hypothesis that the MRPs of gaining and losing a star player are the same in absolute value. For all star player measures aside from Heisman finalists, the MRP of gaining versus losing a star player are of similar magnitude (in absolute value) and the F-statistics imply that they are not statistically different from each other. The asymmetry in the MRP estimates for Heisman finalists is interesting, particularly because the MRP of losing a Heisman finalist is not negative (though statistically insignificant). This makes sense if gaining a Heisman finalist is extremely valuable for the team *and* if these players tend to have an affect on revenues after they leave the school. This idea is supported by the fact that lagged Heisman finalists have large MRP estimates that are highly statistically significant in the previous first-difference and fixed effects regressions. Table 33 reports the estimation results of Equation (2.6) for basketball. For all eight star player measures, the MRP estimates for gaining and losing a star are not statistically different from each other. Since these results indicate that the impact on revenues of gaining and losing a star football or basketball player is symmetric, we can reasonably compare the differences-in-differences MRP estimates in the next section with our previous OLS estimates for star player MRP.[94]

Difference In Difference Results

The differences-in-differences estimates for losing a star football player due to injury from Equation (2.5) are reported in Table 34.[95] Standard errors are clustered by cohort-athletic conference because teams more often play teams in their own conference and if one team

[94]With the exception of Hesiman finalists, however, this measure is not included in the differences-in-differences analysis since there were no treated teams in the sample under this definition of star football player.

[95]The differences-in-differences regressions were run without additional control variables, which allows me to use a slightly larger sample from 2000-2012. In theory, if the treatment is truly random, adding controls would only increase the precision of the estimates and should not change the point estimates. In unreported results, adding additional controls does tend to change the estimates, though not drastically so in most cases. Although the treatment is plausibly random, the likely reason for this is that there are so few observations that adding several additional controls makes it more difficult for the regressions to esimate the coefficients of interest precisely. Therefore, the limited statistical power in these regressions makes it difficult to distinguish between the point estimates changing due to concerns over the random treatment assumption versus the demands on the estimates imposed by additional controls. The results reported in Tables 34 and 35 with controls included are available upon request.

has a star player injured, it will likely enhance the prospects of its competitors, which could lead to them winning more often and generating higher revenues. Panel A of the table reports the results under the definition of treatment that restricts treated teams to having zero star players in year $t+1$, while Panel B contains the results from the more permissive definition of treatment allowing for zero or one star players in year $t+1$.

The first thing to notice that these regressions contain very few observations leading to unreliable standard errors. Furthermore, there are very few treatments that survive under the current definitions of treatment and control groups. Hence, the lack of statistically significant MRP estimates is likely due to low power, rather than the difference-in-difference estimates revealing that star players do not have an impact on revenues. Much like the instrumental variable estimates, the scarcity of injured star players in the data makes it very difficult for the differences-in-differences estimator to detect the true effect of star players on revenues if it does indeed exist. In spite of the low power, these estimates might provide a useful comparison since these estimated coefficients are identified in a completely different way than the OLS estimates using fixed effects and first-differences. For instance, the point estimates in the second and third column of Panel A all lie within the 95% confidence intervals of the MRP estimates for their counterparts estimated under fixed effects and first-differences including the MRP for losing a star player in Tables 13, 19 and 32. Under the slightly more permissive treatment definition in Panel B that contains a few more observations and treatment events, the MRP estimates in all three columns lie within the 95% confidence intervals of their counterpart estimates in the aforementioned tables. We see a similar pattern for the differences-in-differences estimates for losing a star basketball player due to injury in Table 35. The MRP estimates for both measures of star player in both panels are within the 95% confidence interval of the MRP estimates for their counterparts estimated under fixed effects and first-differences including the MRP for losing a star player in Tables 13, 19 and 32. However, we should be even more cautious regarding the basketball results due to the fact that there are under one hundred observations in these regressions and only two or three treatment events.

Although the differences-in-differences estimates suffer from very low power, the identification strategy itself does allow for casual interpretation in a way that is free of the omitted variables worries of the previous fixed effects estimates. Hence, it is somewhat comforting that the differences-in-differences estimates of player MRP give similar results to the MRP estimates for star players using fixed effects. However, we should be cautious in reading too much into these results as the support is very weak given how few injured star players we observe in the data. As with the case using instrumental variables, we would need to observe many more seasons of player data to get enough star players and injuries in order to have enough statistical power for the difference-in-difference approach to provide definitive results.

2.9 Scully Method

In Section 2.5, I presented some evidence that star players generate revenues for their universities through more than just their ability to help the team win games. To provide further insight into a star player's ability to generate revenues through mechanisms other than wins, I estimate the MRP for all eight star basketball player measures using the Scully Method.[96] Recall that the Scully Method assumes the *only* channel through which star players can influence revenues is through their contribution to producing wins. In contrast, the Direct Method I employ above implicitly assumes that star players can impact revenues for reasons unrelated directly to their ability to produce wins. Hence, if most of the star player's ability to impact revenues comes through their contribution to team wins, we would expect the estimates under the Scully Method and the Direct Method to be of comparable

[96] The Scully Method is only employed for basketball as it requires computing an individual player's share of a team's wins, which is very difficult to do in football. This is why the Scully Method is really only used in the context of basketball and baseball where computing a player's share of wins is more feasible.

magnitudes and statistical significance.

The first step in the Scully Method is to compute a player's marginal productivity, which in this context is a player's contribution to team wins. Sports Reference provides an estimate of the number of wins contributed by a player due to his offense and defense, so I use their measure for win shares here.[97] The marginal product for star players is then calculated by simply taking the average of the win shares for star players across teams and years. The second step involves estimating the marginal revenue. Given the following model of basketball revenues

$$y_{i,t} = \eta Wins_{i,t} + X_{i,t}\gamma + \theta_i t + \delta_t + \delta_c + \delta_i + \epsilon_{i,t} \tag{2.7}$$

where $X_{i,t}$ contains the same control variables as before. The only difference between this model and Equation (2.1) is that I have replaced $Stars_{i,t}$ with $Wins_{i,t}$. Hence, the coefficient η is interpreted as the additional revenue associated with and an additional win. I used fixed effects to estimate the revenue model in Equation (2.7) and report just the estimate for η in the top panel of Table 36. The marginal products, computed as described, are reported in the second panel of the table for the eight measures of star players. The bottom panel of Table 36 reports the marginal revenue product using the Scully Method, which is just the marginal revenue estimates multiplied by the marginal products for each star measure.

The Scully Method estimates in Table 36 imply that the MRP of star players ranges from just under $\$100,000$ to as much as $\$150,000$ depending on the star measure used. For instance, the Scully Method estimates for the MRP of players drafted in the NBA is $\$99,321$, which is very close to the estimate of $\$91,030$ reported by Lane et al. (2014) for the same

[97]Please see http://www.sports-reference.com/cbb/about/ws.html for details on how they compute the win share for each player.

measure of star player using the Scully Method. However, the more interesting comparison is between the estimates using the Scully Method and the MRP estimates from the Direct Method in Table 15. The MRPs from the Scully Method are only about 14% to 49% of the MRP estimated from the Direct Method (depending on which star measure considered). On balance, this suggests that a significant portion of a star basketball player's ability to generate revenues for their university comes through mechanisms other than the star player's ability to produce wins.

2.10 Media Exposure

There are many ways that a star football or basketball player might influence university revenues that are not directly tied to their ability to win games. For instance, Texas A&M Foundation President Ed Davis had this to say about the meteoric rise in recognition of Johnny Manziel, Texas A&M's star Quarterback from 2012–2013 and the first Freshman ever to win the Heisman Trophy:

> In an era where we are in, effectively, in the news everywhere and you have a young man like our Quarterback who has been a media magnet and you have the success you have, I do think that euphoria does spill over into success in fundraising.[98]

While Mr. Davis is specifically referring to fundraising for the university, we might think that football and basketball program revenues more generally can be influenced by a star player's media exposure. Consider the following model

$$y_{i,t} = \beta_1 Star_{i,t} + \beta_2 Star_{i,t} \times NewsHits_{i,t} + \beta_3 NewsHits_{i,t} + X_{i,t}\gamma + \theta_i t + \delta_t + \delta_c + \delta_i + \epsilon_{i,t} \tag{2.8}$$

[98] Allen Reed, "Texas A&M breaks fundraising record with $740 million in donations," *The Eagle,* September 17, 2013.

which is identical to Equation (2.1) with the addition of ($NewsHits_{i,t}$), measuring the number of news media pieces about the football or basketball team, and its interaction with the number of star players on the team. This interaction term captures the impact on revenues of an additional news mention when the team has at least one star player. With this modification, the MRP of a star player is now given by $\beta_1 + \beta_2 \times NewsHits$, and since $NewsHits$ is a continuous variable, I will report the MRP for star players at several points in the distribution of news mentions.

The number of times a team is mentioned in the news could also be thought of as a proxy for unobservables involving a university's long term investment in their football or basketball program. This is plausible if we believe that a concerted effort by the university to improve the standing of their team is proxied for by their news media presence. Hence, the model in Equation (2.8) allows me to indirectly assess the argument made by Harvey Perlman that athletic programs generate revenues due to long term investments in the program and the passion or excitement associated with the team. There is, however, another large caveat here. When interpreting the estimation results of Equation (2.8) it is important to note that team news mentions ($NewsHits$) is a bad control since it is also an outcome of the number of star players. Hence, the statistical significance of the MRP estimates should be viewed with caution. However, as long as the bad control is biasing the estimate in the same way for teams across the distribution of news mentions, then the *trend* of star player MRP as a function of news mentions is still informative.

With this caveat in mind, fixed effects estimates of a star football and basketball player's MRP from Equation (2.8) are presented in Figures 3 and 4 for several points in the distribution of news mentions. For football, since touchdowns and yards generate more excitement and are more salient to fans than more technical measures of ability like the PER, I choose to focus just on star measures 1–4.[99] The striking takeaway from Figure 3 is the MRP of a star football player tends to *decrease* the more frequently a team is mentioned in the news.[100] For example, getting an additional star player is likely to be worth less for Nebraska (90th percentile) than for Idaho, Ohio, or Utah State (10th percentile) because Nebraska often has good players and has built a formidable football program and fan base that always generates a lot of revenues. Whereas for Idaho, Ohio, or Utah State, getting an additional star player can be quite valuable for the team; both through the star improving the team's performance and in producing revenues through increased media exposure and generating excitement for the team.

For basketball, I focus on star measures 1–3 and include NBA drafted players as these are likely to be the types of star players generating the most excitement and be the most salient to basketball fans.[101] The results for basketball in Figure 4 are more mixed than is the case with football. The MRP for drafted players decreases the more frequently a team is mentioned in the news wile the MRP under the other three measures is flat or slightly increasing. However, the MRP estimates for drafted players are the only ones that are statistically significant. Overall, the results from controlling for (and interacting) a team's media exposure for basketball and football suggest there might be something to Mr. Perlman's argument if we believe that news mentions are a proxy for university investment into the success of their athletic programs. However, in spite of this observation, it seems clear from the previous MRP estimates in Tables 13 and 15 that star players generate a significant amount of revenues each year for their teams on average.

[99] The star measures 5 and 6 only differ from 4 in how star Quarterbacks are defined and the estimation results for these measures are available upon request.

[100] Although the MRP of star players under measure 4 tends to increase, the estimates are not statistically different from zero for any number of news mentions.

[101] The estimation results for the other basketball star measures are available upon request.

2.10.1 Star Player Media Exposure By Position

Equation (2.8) can be slightly modified to estimate the MRP of star players in specific football positions as follows

$$y_{i,t} = \sum_{pos} \left(\beta_1^{pos} Star_{i,t}^{pos} + \beta_2^{pos} Star_{i,t}^{pos} \times NewsHits_{i,t} \right) + \beta_3 NewsHits_{i,t} \tag{2.9}$$
$$+ X_{i,t}\gamma + \theta_i t + \delta_t + \delta_c + \delta_i + \epsilon_{i,t}$$

where $pos \in \{QB, RB, WR\}$. I limit this analysis to just these three positions since these are the major offensive positions that are likely to the most salient to the fans, hence generating the most excitement.[102] It is worth reiterating that because of the bad control issue, the point estimates should be interpreted with caution, however, the trend in star player MRPs along the news distribution is still informative. Fixed effects estimates of a star football player's MRP by position from Equation (2.8) are presented in Figures 5 and 6 for several points in the distribution of news mentions. The MRPs of star Quarterbacks and Running Backs tend to decrease the more frequently a team is mentioned in the news. The same is true for All-American and Heisman nominated Wide Receivers. However, the trend is increasing for Wide Receivers that were Heisman finalists or among the top 10 in touchdowns or yards. For the former case this might be because Wide Receivers are infrequently nominated for the Heisman relative to other positions, only four of which were Heisman finalists.[103] Hence, these four players might really be so much better than an average Wide Receiver that they would generate higher revenues for any team, even augmenting revenues for well known teams. Likewise, a Wide Receiver among the top 10 in touchdowns or yards might also augment revenues through generating bigger, more exciting plays with longer and more spectacular receptions. Although potentially interesting, these

[102] Also, the only measure of star that includes any positions other than these three is the All-American measure and the MRP for All-Americans in other positions were not statistically significant in the prior analysis.

[103] Over the sample 2003-2012, only 11% of players nominated for the Heisman are Wide Receivers while 28% were Running Backs and 51% were Quarterbacks. The four Wide Receiver Heisman finalists are Justin Blackmon, Larry Fitzgerald, Marqise Lee and Michael Crabtree.

speculations require further investigation. Overall, the position specific regressions give results similar to the aggregate star regressions in the previous section, implying that having a star player is worth less for teams that are more frequently mentioned in the news.

2.11 Conclusion

The NCAA has long prevented college athletes from being paid directly for their athletic ability. This practice has been defended under the guise of amateurism, which seems at odds with the public perception that college athletes generate millions of dollars in revenues for their universities and receive little in return. Increasingly, the NCAA's claims of amateurism appear anachronistic as the business of collegiate athletics has begun to appear indistinguishable from a professional sports organization. This observation has led many people to question the fairness of restricting payment to players, which has pointedly manifest itself in a series of recent lawsuits. One recent lawsuit claims that the NCAA's practice of price-fixing collegiate players' compensation violates U.S. anti-trust laws under the Sherman Act. Central to this claim is that the NCAA restricts an athletes compensation to grant-in-aid, limiting competition and capturing the rents that should rightfully go to players who generate millions of dollars a year in revenues for their universities. This argument implies that if a competitive labor market for college players existed, they would be able to capture a large proportion of these rents as players would be compensated according to their marginal revenue product. In order to inform the debate, this paper provides estimates for a college football and basketball player's marginal revenue product by examining the contribution of star players to athletic program revenues.

Overall, I find the marginal revenue product of a Division 1 FBS college football player is just over \$1.2 million for All-American players, while the marginal revenue product of Heisman finalists and Heisman nominees are \$2.1 and \$1.8 million respectively. Also, the marginal revenue product is around $\$600,000$ for football players ranked among the top 10 by performance statistics. Looking at individual positions, I find marginal revenue products for star Quarterbacks ranging from $1 to $4.6 million a year on average and $2.9 million for star Wide Receivers. For basketball, I find that players who won the Wooden Award, Naismith Award, or were named the most outstanding player in the NCAA Tournament are worth up to $1.1 million a year while players named to the All American First Team are worth up to $\$654,000$. Also, players that were drafted, a top 5 or top 10 NBA draft pick, or were in the top 10 or 20 points scorers in a season are worth up to around $\$200,000-\$400,000$ a year. These findings suggest that star football and basketball players are worth a significant amount to the institutions whose teams they play for, which gives us some insight into the magnitude of the economic rents generated by star players that are being captured by universities with Division 1 football and basketball programs.

In response to claims of unfairness, some have argued that the reason top collegiate athletics programs generate significant revenues is a function of the university's long term investment in these programs, fan enthusiasm, and alumni excitement for the team rather than individual player efforts. To indirectly asses this claim, I use the number of times a football or basketball team is mentioned in the news media as a measure of excitement for the team. In addition, this measure is likely a reasonable proxy for a university's long term investment in their football or basketball programs. Incorporating this measure into the analysis reveals that star football and basketball players tend to be worth less to teams who are more frequently mentioned in the news. This result provides some tentative support to the counter-argument, however, even in light of this observation it seems clear that star football and basketball players generate a significant amount of revenues each year for their universities. Ultimately, the normative question whether college athletes should be compensated beyond what the current NCAA rules allow must be decided by the players, fans, and institutions that make college athletics possible. This paper provides a quantitative analysis to aid and inform that discussion.

Table 8

College Football Summary Statistics

This table reports summary statistics for varibles used in the regression analysis over the sample period 2003-2012.

	Mean	Std. Dev.	Min	Max	10%	90%
Football Program Revenues†	23,662,588	19,671,888	2,392,553	111,329,618	5,346,434	54,708,011
Wins	6.59	3.03	0	14	2.00	11.00
Number of Bowl Games	5.55	2.88	0	10	1.00	9.00
Number of Bowl Games Won	2.79	2.00	0	8	0.00	6.00
Strength of Schedule	0.58	4.24	-10.89	9.68	-5.48	5.74
Points Allowed Per Game	25.87	6.82	8.20	47.60	17.30	35.15
Yards Allowed Per Game	371.98	57.33	183.60	526.10	298.85	450.05
Passing Yards Allowed Per Game	220.33	34.83	111.50	340.40	175.85	266.40
Passing TDs Allowed Per Game	1.52	0.49	0.40	3.30	0.90	2.20
Rushing TDs Allowed Per Game	151.65	39.39	43.40	276.80	102.60	207.10
Rushing Yards Allowed Per Game	1.49	0.61	0.20	4.10	0.80	2.30
Avg. Distance From Good Players‡	1,022	271	747	1,833	801	1,529
Undergraduate Population	19,985	8,708	2,672	59,382	8,962	31,552
Per-Capita Personal Income†	39,615	4,911	29,081	56,713	34,086	46,221
Growth in Per-Cap. Personal Inc.	1.24	2.52	-11.26	10.22	-1.88	4.04
City Population	336,022	622,655	12,731	3,857,799	28,756	750,663
State Population	10,723,073	9,462,480	503,453	38,041,430	2,712,335	24,801,761
Number of News Articles	1,025	994	0	7,368	213	2,332
Observations	1,040					
Number of Teams	104					

†: Real 2012 U.S. Dollars. ‡: Miles.

Table 9

College Basketball Summary Statistics

This table reports summary statistics for varibles used in the regression analysis over the sample period 2003-2012.

	Mean	Std. Dev.	Min	Max	10%	90%
Basketball Program Revenues†	3,927,306	4,623,809	165,471	44,093,915	882,557	9,982,928
Wins	16.70	6.48	0	38	8	25
NCAA Tournament Appearances	0.74	0.94	0	4	0	2
NCAA Tournament Round 2	0.68	1.03	0	5	0	2
NCAA Tournament Sweet 16	0.44	0.88	0	5	0	2
NCAA Tournament Elite 8	0.14	0.49	0	3	0	0
NCAA Tournament Final 4	0.07	0.29	0	2	0	0
NCAA Tournament Final	0.04	0.20	0	2	0	0
NCAA Tournament Winner	0.04	0.24	0	2	0	0
Teams in Athletic Conference	10.95	1.97	4	16	8	13
AP Ranked Teams in Conference	1.04	1.62	0	7	0	3
NCAA Tournament Teams in Conference	2.45	2.15	0	11	1	6
Final Four Teams in Conference	0.17	0.43	0	2	0	1
Strength of Schedule	0.46	5.20	-13.38	12.04	-6.04	7.66
Avgerage Distance From Good Players‡	991	303	704	1,880	744	1,638
Undergraduate Population	13,602	9,349	1,157	59,382	3,182	26,408
Per-Capita Personal Income†	41,525	6,140	29,081	60,748	34,670	51,441
Growth in Per-Capita Personal Income	1.25	2.34	-11.26	10.22	-1.76	3.93
City Population	507,864	1,357,731	328	8,336,697	13,864	817,159
State Population	11,032,143	9,384,200	503,453	38,041,430	2,783,785	24,309,039
Number of News Articles	273	407	0	3,946	35	705
Observations	2,820					
Number of Teams	282					

†: Real 2012 U.S. Dollars. ‡: Miles.

Table 10

College Football Star Player Measures

This table reports the number of star players and their relative frequency in the data over the sample period 2003-2012 for six different measures of star players: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The column %Plyrs denotes the frequency of star players (N/Total Number of Player-Years). The column %Pos denotes the frequency of star players relative to the total number of player-years in positions eligible for that particular star measure given how the star player measures are defined. So for star measures (2-6) the relevant denominator is the total number of player-years for Quarterbacks, Running Backs and Wide Receivers while the denominator for (1) includes all player-years since all positions are eligible to be designated an All American player. The numbers in parentheses denote the percentage of players designated as a star player relative to the total number of players in their position.

	Aggregated			By Position						
Star Measure	N	% Plyrs	%Pos	QB	RB	WR	TE	OL	K	P
(1) AA Team	256	0.45	0.45	11	27	26	11	47	10	10
				(0.37)	(0.42)	(0.31)	(0.35)	(1.43)	(0.52)	(0.91)
(2) HF	46	0.08	0.26	28	14	4				
				(0.94)	(0.22)	(0.05)				
(3) HN	88	0.15	0.50	50	27	11				
				(1.67)	(0.42)	(0.13)				
(4) TDsYds	471	0.83	2.65	137	158	176				
				(4.58)	(2.48)	(2.10)				
(5) PERTDsYds	514	0.98	2.90	180	158	176				
				(6.02)	(2.48)	(2.10)				
(6) PER	435	0.77	2.45	131	158	176				
				(3.38)	(2.48)	(2.10)				
							LB	DB	DL	
(1) AA Team							31	42	41	
Continued							(0.37)	(0.39)	(0.44)	

Table 11

College Basketball Star Player Measures

This table reports the number of star players and their relative frequency in the data over the sample period 2003-2012 for eight different measures of star players: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The column % All Plyrs denotes the frequency of star players (N/Total Number of Player-Years).

Star Measure	N	% All Players
(1) Award Winners	19	0.05
(2) All American First Team	49	0.12
(3) All Americans	105	0.27
(4) NBA Drafted	420	1.06
(5) NBA Top 5 Draft Pick	43	0.11
(6) NBA Top 10 Draft Pick	83	0.21
(7) Top 10 Points Scorers	90	0.23
(8) Top 20 Points Scorers	178	0.45

Table 12

Ex-Ante Star Player Measures

This table reports the number of ex-ante star players and their relative frequency in the data over the sample period 2005-2012. Top Rivals is the number of players with a Rivals.com ranking of 6.1, High Rivals is the number of players with a Rivals.com ranking of 6.0 or better, and 5 Star is the number of players with a 5-star Rivals.com ranking. The measures denoted with an "OP" are identically defined but are restricted to the offensive positions of Quarterback, Runningback and Wide Reciever. The column % Plyrs denotes the frequency of star players (N/total number of player-years), where the denominator in the case of the "OP" measures only includes the total number of player-years for offensive positions.

Football Star Measure	N	% Players
Top Rivals	565	1.15
High Rivals	1,355	2.76
5 Star	663	1.35
Top Rivals OP	246	1.71
High Rivals OP	522	3.63
5 Star OP	292	2.03
Basketball Star Measure	**N**	**% Players**
5 Star	422	1.34

Table 13

Marginal Revenue Product of Star College Football Players. This table reports fixed effects regression estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The full estimation results are reported in Table 38 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	1246194.1***	2110456.4**	1772393.3***	635939.4**	620915.0**	634448.8**
	(371109.5)	(933544.5)	(557169.9)	(273501.0)	(258687.2)	(283630.8)
Stars_{t-1}	784531.3*	1541987.4**	2125693.1***	463500.0**	482399.8**	629070.6***
	(407013.3)	(746867.3)	(613806.8)	(209543.1)	(199374.2)	(222252.8)
Stars_{t-2}	549369.2	-211988.4	135553.5	2163.8	131353.3	156726.8
	(409714.8)	(625430.4)	(497226.6)	(191799.8)	(217898.7)	(230384.4)
Wins_{t-1}	-33715.1	2350.5	-65521.4	17886.1	10689.7	2674.8
	(105185.3)	(95311.6)	(101668.3)	(102868.0)	(101990.9)	(101220.6)
Wins_{t-2}	47950.9	102288.3	84403.1	94650.6	77305.9	74126.7
	(56749.6)	(61649.3)	(62019.0)	(66211.5)	(68658.6)	(65450.8)
CoachCareer_{t-1}	2571657.5	1933681.0	2473963.0	1252014.5	1252673.2	1423088.7
	(2077061.6)	(2066798.6)	(2083839.1)	(2063261.0)	(2066246.2)	(2077016.9)
BowlGame_{t-1}	862673.1*	696357.4	805688.7*	612201.2	626535.5	622163.7
	(463602.8)	(443760.2)	(457479.2)	(458303.6)	(455531.3)	(452238.2)
BowlWin_{t-1}	-367095.4	-228156.7	-186535.8	-379685.7	-393601.2	-391951.8
	(417701.8)	(426506.3)	(401965.8)	(424937.9)	(427281.8)	(427480.3)
Distance	-24893.5	-26074.5	-25418.8	-20941.5	-20871.2	-21590.8
	(16516.5)	(17347.0)	(17021.0)	(17282.3)	(17333.0)	(17225.4)
PerCapPI	184142.6	257071.2	271520.4	218391.4	212482.4	204275.8
	(319267.5)	(335018.5)	(322485.3)	(329132.8)	(328377.7)	(322979.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.773	0.775	0.779	0.774	0.774	0.774
Adjusted R^2	0.972	0.972	0.972	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14

Marginal Revenue Product of Star College Football Players by Position. This table reports fixed effects regression estimates of a star football player's marginal revenue product from Model (2.2) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. One and two year lags for star players are included, but not reported here, please see Table 39 in Appendix A.7 for the full results.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDYds	(6) PER
Star QB	4608930.9***	3471509.8**	2214355.5**	1019893.4**	924894.5**	850420.6*
	(1164765.0)	(1351570.5)	(934112.1)	(478396.0)	(392270.5)	(481015.0)
Star RB	301788.4	608943.1	1048518.4	488427.7	421584.8	444569.6
	(631539.7)	(1309714.5)	(915890.6)	(429620.5)	(414200.9)	(418953.7)
Star WR	2905696.8**	-767266.6	2472387.2	464649.9	423843.9	576679.4
	(1405377.0)	(3344772.8)	(1949165.7)	(536098.5)	(544325.4)	(516914.8)
Star TE	1276488.1					
	(1060995.6)					
Star OL	1817052.2					
	(1902022.5)					
Star K	-1413320.6					
	(917291.1)					
Star P	2254073.1					
	(2391757.8)					
Star LB	1343434.9					
	(1161464.0)					
Star DB	900250.4					
	(809392.0)					
Star DL	-152692.0					
	(1029483.9)					
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
1Y and 2Y Star Lags	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.784	0.777	0.782	0.774	0.775	0.776
Adjusted R^2	0.972	0.972	0.973	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15

Marginal Revenue Product of Star College Basketball Players. This table reports fixed effects regression estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The full estimation results are reported in Table 40 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1087765.3**	654710.8***	345336.8**	204304.3**	382382.2**	402533.9**	310260.3*	319721.4**
	(493080.3)	(194042.4)	(171755.6)	(88775.4)	(191897.4)	(192852.0)	(181824.4)	(145587.1)
Stars_{t-1}	217558.3	12327.7	88669.0	-11202.2	186547.7	-5263.1	14561.2	30787.2
	(374357.0)	(291240.1)	(177561.3)	(88077.2)	(294223.2)	(228566.6)	(102755.7)	(81964.0)
Stars_{t-2}	205491.5	149084.8	207909.7	224483.7**	252300.1	106031.9	174220.5	80851.8
	(336928.1)	(215135.9)	(157622.5)	(100847.0)	(245098.3)	(202592.1)	(113390.1)	(85780.5)
Wins_{t-1}	5500.7	4737.6	4803.9	6675.7	4912.5	5211.9	5529.2	4768.9
	(4740.8)	(4654.8)	(4704.4)	(4620.0)	(4565.3)	(4611.5)	(4768.7)	(4879.6)
Wins_{t-2}	11700.8***	11033.7**	10379.1**	7470.9	11046.7***	11099.0***	10877.3**	10851.1**
	(4346.4)	(4372.0)	(4388.4)	(4631.2)	(3932.6)	(4106.4)	(4501.2)	(4605.0)
$\text{CoachCarTourn}_{t-1}$	53036.4***	53587.8***	52917.5***	53109.5***	53300.7***	54220.0***	54132.1***	52295.5***
	(16309.4)	(16423.3)	(16448.0)	(16397.5)	(16396.1)	(16327.9)	(16345.8)	(16446.8)
NCAATourn_{t-1}	166471.4**	169729.4**	164773.6**	170940.6**	166791.3**	159770.3**	159670.5**	159186.5**
	(75438.0)	(74536.1)	(74413.7)	(76855.4)	(73208.1)	(75031.2)	(74594.7)	(75231.3)
Champ_{t-1}	1766340.3**	1900785.4***	1899835.5***	2040793.9***	1793747.7**	1773651.1**	1822732.5***	1868723.7***
	(862499.7)	(574563.6)	(657183.3)	(647180.9)	(752011.7)	(736771.7)	(617623.3)	(618632.4)
Distance	-1186.9	-1003.1	-1076.7	-1295.0	-1243.4	-1145.3	-1390.8	-1233.8
	(1555.8)	(1564.4)	(1548.8)	(1571.5)	(1593.4)	(1568.2)	(1542.9)	(1532.9)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.670	0.669	0.668	0.672	0.668	0.669	0.668	0.669
Adjusted R^2	0.968	0.968	0.968	0.969	0.968	0.968	0.968	0.968

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16

Marginal Revenue Product of Star College Football Players - Wins Included. This table reports fixed effects regression estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The full estimation results are reported in Table 43 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	926451.1**	1522818.2*	1177237.5**	273485.5	256650.6	277127.5
	(402026.1)	(889228.6)	(544071.6)	(305633.1)	(292662.4)	(304313.0)
Wins	274939.7***	348969.4***	351564.9***	353074.9***	354350.2***	359789.8***
	(74995.2)	(79970.3)	(78791.9)	(97875.9)	(98355.4)	(91981.8)
Wins_{t-1}	-7345.1	23825.2	-49181.1	42722.7	35500.1	26959.1
	(106403.2)	(96990.4)	(101631.9)	(104352.5)	(103815.1)	(102155.3)
Wins_{t-2}	111438.2*	149553.4**	133762.7**	143999.7**	128650.6*	124482.8*
	(61823.0)	(65103.8)	(65590.4)	(69353.3)	(71157.5)	(67503.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.779	0.781	0.785	0.780	0.780	0.780

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17

Marginal Revenue Product of Star College Football Players by Position - Wins Included. This table reports fixed effects regression estimates of a star football player's marginal revenue product from Model (2.2) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The full estimation results are reported in Table 44 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDYds	(6) PER
Star QB	4002896.6***	2613205.7*	1338255.8	426270.7	344168.7	381371.0
	(1144409.0)	(1322656.6)	(921253.7)	(504839.4)	(424145.3)	(479613.7)
Star RB	-71395.5	287602.6	822523.3	164893.3	117441.0	127832.2
	(626403.8)	(1260993.0)	(914857.0)	(446548.7)	(437817.1)	(441013.1)
Star WR	2671726.0*	-430341.1	2275417.0	250983.5	230554.0	272862.4
	(1379730.4)	(3370752.1)	(1911482.0)	(534304.1)	(543821.9)	(521004.1)
Star TE	709435.3					
	(1101329.7)					
Star OL	1441320.6					
	(1894931.1)					
Star K	-1713721.1*					
	(943726.6)					
Star P	2240380.6					
	(2448445.7)					
Star LB	1100736.3					
	(1199072.9)					
Star DB	514531.4					
	(879917.8)					
Star DL	-343706.0					
	(1057113.1)					
Wins	273964.8***	330986.2***	357280.0***	347714.3***	345097.5***	352589.0***

	(73651.1)	(76827.9)	(76999.7)	(99527.1)	(99837.8)	(91104.1)
Wins_{t-1}	-26800.7	29252.4	-68389.3	38309.6	32381.0	3188.5
	(107121.3)	(98462.6)	(104010.1)	(108974.8)	(108002.9)	(107336.9)
Wins_{t-2}	105240.5*	144613.5**	129268.5*	144210.0*	117311.1	114024.1
	(62154.1)	(66425.7)	(67525.4)	(75426.6)	(80101.5)	(72453.8)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.790	0.783	0.788	0.780	0.781	0.782

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18

Marginal Revenue Product of Star College Basketball Players - Wins Included. This table reports fixed effects regression estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The full estimation results are reported in Table 45 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	966953.5*	561750.5***	255794.2	165147.4*	276439.2	314342.4*	239950.0	261080.0*
	(491931.7)	(188740.4)	(168360.1)	(88732.0)	(191644.3)	(189002.7)	(179922.3)	(144643.1)
Stars_{t-1}	226425.3	13283.8	88317.9	-3280.9	167345.1	-1644.5	22131.5	33415.2
	(380815.1)	(285594.4)	(174900.9)	(87014.6)	(287882.3)	(224140.2)	(102344.0)	(82020.7)
Stars_{t-2}	203893.4	165585.0	205185.0	221952.9**	234977.4	108587.0	159468.7	69587.1
	(336693.0)	(218117.7)	(155300.2)	(100080.7)	(243293.3)	(199662.2)	(113475.9)	(86536.2)
Wins	16401.4***	16095.1***	16532.0***	14674.9***	17132.9***	16137.1***	17154.5***	16032.2***
	(4022.4)	(4050.8)	(4061.7)	(3968.5)	(4304.9)	(4126.2)	(4226.7)	(4179.2)
Wins_{t-1}	4748.5	4102.8	4100.7	5912.3	4171.2	4528.4	4721.5	4122.7
	(4697.1)	(4621.6)	(4668.8)	(4595.2)	(4522.4)	(4586.8)	(4724.2)	(4828.4)
Wins_{t-2}	15495.5***	14761.6***	14219.9***	10899.3**	15062.1***	14880.7***	15002.4***	14752.4***
	(4544.6)	(4571.7)	(4520.0)	(4782.4)	(4172.7)	(4291.8)	(4736.9)	(4854.2)
$\text{CoachCarTourn}_{t-1}$	53608.3***	53939.5***	53237.4***	53561.2***	53678.2***	54457.3***	54653.0***	52980.0***
	(16243.8)	(16323.8)	(16347.0)	(16315.1)	(16304.6)	(16256.2)	(16259.3)	(16376.0)
NCAATourn_{t-1}	165630.5**	167951.2**	165258.0**	172095.1**	166695.3**	161106.1**	159724.4**	159488.4**
	(74989.6)	(74251.6)	(74014.2)	(76384.5)	(72835.6)	(74381.4)	(74244.2)	(74821.3)
Champ_{t-1}	1804407.2**	1954931.9***	1952856.5***	2079971.4***	1858425.7**	1853390.6**	1883220.4***	1914658.2***
	(852024.8)	(585288.6)	(657342.2)	(643846.0)	(747454.4)	(726504.3)	(618545.2)	(619006.2)
Distance	-1028.3	-894.8	-942.9	-1182.5	-1082.4	-1007.9	-1205.4	-1075.8
	(1538.6)	(1543.9)	(1533.3)	(1555.5)	(1568.2)	(1549.4)	(1527.0)	(1521.5)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.672	0.672	0.671	0.674	0.670	0.671	0.670	0.671
Adjusted R^2	0.969	0.969	0.968	0.969	0.968	0.968	0.968	0.969

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19

Marginal Revenue Product of Star College Football Players. This table reports first-difference estimates of a star football player's marginal revenue product from Model (2.3) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The full estimation results are reported in Table 46 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
ΔStars_t	948869.0***	1469685.8*	1445711.1***	779553.1***	748806.3***	750360.7***
	(349418.3)	(828796.5)	(506010.5)	(235433.4)	(225132.4)	(254279.4)
$\Delta \text{Stars}_{t-1}$	709250.0*	1649626.2**	2120098.8***	573737.5***	590639.4***	739697.0***
	(402677.7)	(674256.7)	(569801.0)	(207958.1)	(208535.9)	(223208.1)
$\Delta \text{Stars}_{t-2}$	163983.3	49332.1	194599.5	-55141.1	76767.2	220992.2
	(352823.6)	(576912.1)	(441350.4)	(156582.1)	(180291.6)	(192410.0)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	936	936	936	936	936	936
R^2	0.145	0.155	0.169	0.168	0.165	0.162

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20

Marginal Revenue Product of Star College Basketball Players. This table reports first-difference regression estimates of a star basketball player's marginal revenue product from Model (2.3) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The full estimation results are reported in Table 47 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔStars_t	1244669.4***	682364.7***	332745.2	197634.8**	475602.4**	435118.6**	369001.0*	395939.8**
	(473789.8)	(152435.6)	(204309.7)	(90979.0)	(188524.0)	(174028.1)	(204126.7)	(162427.6)
$\Delta \text{Stars}_{t-1}$	1316327.3***	355506.6*	157342.8	53072.7	328429.3	271346.3	129652.0	177974.9*
	(339865.8)	(197409.3)	(157492.2)	(87034.0)	(254837.0)	(187689.1)	(123510.3)	(104788.6)
$\Delta \text{Stars}_{t-2}$	605049.6	270524.5	37812.9	197711.5**	125740.9	34561.9	111437.7	102171.0
	(369234.7)	(188809.1)	(159556.9)	(99526.1)	(231342.9)	(200534.0)	(115025.0)	(96238.5)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2819	2819	2819	2819	2819	2819	2819	2819
R^2	0.103	0.0990	0.0951	0.106	0.0950	0.0967	0.0952	0.100

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21

Marginal Revenue Product of Star College Football Players. This table reports OLS estimates of a star football player's marginal revenue product from Model (2.4) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The full estimation results are reported in Table 48 in Appendix A.7

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	1079047.5***	1238360.9	1133259.8*	688562.2***	682939.7***	653164.6***
	(289289.4)	(896004.8)	(578029.1)	(215182.7)	(207103.7)	(236700.4)
Revenues$_{t-1}$	0.634***	0.632***	0.634***	0.631***	0.629***	0.629***
	(0.0518)	(0.0469)	(0.0466)	(0.0463)	(0.0465)	(0.0468)
Revenues$_{t-2}$	0.0682	0.0772	0.0802	0.0779	0.0783	0.0789
	(0.0633)	(0.0603)	(0.0600)	(0.0604)	(0.0602)	(0.0604)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.972	0.972	0.972	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22

Marginal Revenue Product of Star College Basketball Players. This table reports OLS estimates of a star basketball player's marginal revenue product from Model (2.4) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The full estimation results are reported in Table 49 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1206300.1**	635196.1**	341945.7	247469.1**	527306.9**	421527.9*	414020.6**	370848.7**
	(501780.2)	(245445.2)	(212881.3)	(99151.5)	(236665.1)	(254394.8)	(190465.1)	(155549.9)
Stars_{t-1}	462913.2	54083.6	-19918.0	-38558.9	198894.2	17053.7	-42974.3	-10924.1
	(315212.3)	(279577.9)	(189781.5)	(88269.1)	(325219.3)	(246099.5)	(126430.0)	(78065.5)
Stars_{t-2}	-413247.1	26767.6	-50709.7	164020.0*	-59523.1	-168030.2	8130.3	-91041.0
	(362317.1)	(227605.2)	(213869.0)	(98863.0)	(369112.6)	(261677.2)	(194254.3)	(120111.6)
Revenues_{t-1}	0.448***	0.441***	0.441***	0.439***	0.441***	0.442***	0.441***	0.443***
	(0.0823)	(0.0813)	(0.0816)	(0.0813)	(0.0816)	(0.0818)	(0.0814)	(0.0813)
Revenues_{t-2}	0.192***	0.193***	0.190***	0.185***	0.190***	0.189***	0.189***	0.189***
	(0.0297)	(0.0290)	(0.0291)	(0.0293)	(0.0301)	(0.0299)	(0.0293)	(0.0293)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
R^2	0.963	0.963	0.963	0.963	0.963	0.963	0.963	0.963

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23

College Basketball Summary Statistics

This table reports summary statistics for varibles used in the regression analysis on the subset of institutions with both Division 1 men's basketball and Division 1 FBS football programs over the sample period 2003-2012.

	Mean	Std. Dev.	Min	Max	10%	90%
Basketball Program Revenues†	6,755,197	5,698,829	436,805	44,093,915	1,343,627	14,287,537
Wins	18.71	6.54	3	38	10	27
NCAA Tournament Appearances	0.90	1.00	0	4	0	2
NCAA Tournament Round 2	1.08	1.23	0	5	0	3
NCAA Tournament Sweet 16	0.76	1.06	0	4	0	2
NCAA Tournament Elite 8	0.29	0.68	0	3	0	1
NCAA Tournament Final 4	0.13	0.40	0	2	0	1
NCAA Tournament Final	0.07	0.25	0	1	0	0
NCAA Tournament Winner	0.08	0.36	0	2	0	0
Teams in Athletic Conference	11.65	1.69	8	16	9	14
AP Ranked Teams in Conference	1.95	1.78	0	7	0	4
NCAA Tournament Teams in Conference	3.72	2.31	1	11	1	7
Final Four Teams in Conference	0.31	0.54	0	2	0	1
Strength of Schedule	4.19	4.10	-8.78	12.04	-1.77	8.53
Avgerage Distance From Good Players‡	1,000	291	722	1,833	762	1,578
Undergraduate Population	20,084	8,856	1,826	59,382	9,096	31,746
Per-Capita Personal Income†	39,781	5,275	29,081	60,748	34,193	46,603
Growth in Per-Capita Personal Income	1.21	2.51	-11.26	10.22	-1.94	4.04
City Population	370,786	917,482	12,004	8,336,697	28,704	668,877
State Population	10,732,329	9,224,355	503,453	38,041,430	2,723,421	24,309,039
Observations	1,190					
Number of Teams	119					

†: Real 2012 U.S. Dollars. ‡: Miles.

Table 24

Marginal Revenue Product of Star College Basketball Players at Institutions With Both Division 1 Basketball and FBS Football Programs. This table reports fixed effects estimates of a star basketball player's marginal revenue product from Model (2.1) on the subset of insitutions that field both Division 1 men's basketball and FBS football teams over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The full estimation results are reported in Table 50 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1114532.9**	707635.5***	375421.7*	234764.9**	367265.6*	394478.2*	505290.1**	407254.8**
	(551453.9)	(212897.4)	(191674.2)	(103653.3)	(190847.6)	(208448.9)	(238299.5)	(203111.9)
Stars_{t-1}	104860.9	32287.0	113548.0	-12997.5	251296.3	-16303.1	130230.0	94249.4
	(455975.9)	(340511.3)	(213514.4)	(108401.2)	(321824.0)	(260249.4)	(148243.0)	(134762.3)
Stars_{t-2}	150825.9	160804.2	247456.9	234387.1**	300116.0	111073.8	124997.9	-3839.7
	(387708.2)	(245773.4)	(189350.9)	(117911.1)	(236329.2)	(210690.6)	(152950.6)	(133744.6)
Wins_{t-1}	12154.8	10160.2	10750.6	15136.5	10211.4	11411.3	10771.6	11238.3
	(11816.8)	(11670.9)	(11931.7)	(11751.4)	(11609.2)	(11671.5)	(12034.0)	(12206.7)
Wins_{t-2}	21788.9**	19898.4**	18709.4*	13020.9	19679.9**	20551.7**	19042.6*	24763.4**
	(9552.0)	(9880.7)	(10015.8)	(10982.6)	(9275.3)	(9732.1)	(10592.7)	(10784.8)
$\text{CoachCarTourn}_{t-1}$	51009.4***	51767.4***	51052.1**	52421.2***	52211.4***	53427.2***	49956.9**	52697.7***
	(19438.7)	(19446.2)	(19578.9)	(19398.8)	(19642.8)	(19506.6)	(19720.0)	(19559.4)
NCAATourn_{t-1}	266317.1*	270618.4**	259113.4*	266463.9*	264986.5**	252185.6*	273269.3**	240664.6*
	(135093.2)	(133685.7)	(133819.4)	(136466.6)	(130821.9)	(135882.6)	(133577.5)	(134010.9)
Champ_{t-1}	1842348.1*	1895952.4***	1888025.9***	2004486.5***	1749210.4**	1758590.7**	1841494.2***	1718239.4***
	(964111.2)	(632171.8)	(719208.1)	(705646.0)	(834333.3)	(808820.0)	(681780.7)	(608902.7)
Distance	-944.2	-724.4	-897.0	-817.3	-1083.7	-972.4	-741.9	-1208.4
	(4392.0)	(4420.9)	(4372.9)	(4389.2)	(4499.1)	(4459.4)	(4375.0)	(4421.1)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1190	1190	1190	1190	1190	1190	1190	1190
Within R^2	0.686	0.686	0.685	0.690	0.685	0.685	0.687	0.688
Adjusted R^2	0.957	0.957	0.957	0.958	0.957	0.957	0.958	0.958

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25

Marginal Revenue Product of Ex-Ante Star College Football Players. This table reports fixed effects estimates of an ex-ante star football player's marginal revenue product from Model (2.1) over the sample period 2005-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) Top Rivals.com Recruits (Rivals.com rating of 6.1), (2) High Rivals.com Recruits (Rivals.com rating of 6 or better), (3) Rivals.com Five Star Rated Recruit. The last three measures (4-6) are the same as (1-3) except isolated to only the Offensive Positions (OP) of Quarterback, Running Back, and Wide Receiver. The full estimation results are reported in Table 51 in Appendix A.7.

	(1) Top Riv	(2) High Riv	(3) 5 Star	(4) Top Riv OP	(5) High Riv OP	(6) 5 Star OP
Stars	291572.2	100964.3	452130.7	844171.8	208951.9	829356.5
	(475612.5)	(258900.2)	(489486.5)	(735283.7)	(515711.0)	(739502.1)
Stars_{t-1}	88005.2	-238273.1	447989.4	-478993.5	-315699.6	-366974.8
	(359552.0)	(263211.1)	(287902.5)	(422948.6)	(293817.5)	(405187.3)
Stars_{t-2}	477074.7	437018.8	138076.7	174979.9	638371.0	-227883.6
	(652932.0)	(388483.6)	(505997.3)	(794618.4)	(558654.2)	(708797.3)
Wins_{t-1}	90967.2	85302.2	61987.1	108444.2	108437.7	93652.0
	(102195.1)	(93046.1)	(102009.4)	(95976.1)	(92164.1)	(96464.9)
Wins_{t-2}	25800.3	40110.4	18517.3	62339.0	58695.5	68866.7
	(70556.3)	(72178.3)	(67634.0)	(66038.7)	(69015.4)	(64484.4)
CoachCareer_{t-1}	68154.7	139515.6	49078.6	-793740.5	-715548.8	-655175.2
	(1985339.3)	(2033843.8)	(2013093.7)	(2029059.8)	(2018001.2)	(2026444.9)
BowlGame_{t-1}	470586.9	509647.8	546839.3	402070.1	411870.6	450003.5
	(434039.5)	(411079.8)	(443868.3)	(448999.1)	(424706.8)	(434029.7)
BowlWin_{t-1}	-368951.0	-373960.5	-355865.7	-276082.9	-342034.9	-248283.7
	(462170.7)	(448379.6)	(459427.9)	(443369.3)	(442506.3)	(451776.9)
Distance	-62052.5**	-62379.8**	-56486.6*	-59148.7*	-60412.0**	-58522.0*
	(31220.9)	(30441.2)	(32607.0)	(29997.7)	(29340.7)	(30238.3)
PerCapPI	278907.1	258284.5	242587.2	164184.5	206456.1	169113.4
	(355905.3)	(348088.1)	(347007.7)	(365438.6)	(369615.6)	(360989.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	832	832	832	832	832	832
Within R^2	0.745	0.744	0.747	0.747	0.747	0.748
Adjusted R^2	0.977	0.977	0.978	0.977	0.977	0.977

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26

Marginal Revenue Product of Ex-Ante Star College Basketball Players. This table reports fixed effects estimates of an ex-ante star basketball player's marginal revenue product from Model (2.1) over the sample period 2005-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for the ex-ante star measure using the Rivals.com Five Star Rated Recruits are reported. The full estimation results are reported in Table 52 in Appendix A.7.

	(1) 5 Star	
Stars	317810.8*	(172843.9)
Stars_{t-1}	-153329.7	(111547.7)
Stars_{t-2}	275291.1***	(98460.6)
Wins_{t-1}	1000.3	(5259.5)
Wins_{t-2}	8061.1	(5549.4)
$\text{CoachCarTourn}_{t-1}$	72803.8***	(25416.2)
NCAATourn_{t-1}	222111.5**	(96680.5)
Champ_{t-1}	2081114.0**	(813929.5)
Distance	-427.9	(1880.0)
Team Fixed Effects	Yes	
Year Fixed Effects	Yes	
Confr. Fixed Effects	Yes	
N	2256	
Within R^2	0.641	
Adjusted R^2	0.972	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27

Marginal Revenue Product of Expected and Unexpected Star College Football Players. This table reports fixed effects estimates of the marginal revenue products of expected and unexpected star football players from Model (2.1) over the sample period 2005-2012. Star players are measured according to one of six ex-post performance metrics: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The number of star players on a team are then decomposed into "expected" and "unexpected" star players. Expected stars are those who are stars as measured by ex-post performance who were also top Rivals.com recruits (rated as a 6.1 by Rivals.com). Unexpected stars are those who are stars as measured by ex-post performance who were not rated as a top Rivals.com recruit. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. The full estimation results are reported in Table 53 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Expected Stars	2720071.0***	3734700.3***	2168631.6	1554102.7	1465080.5	1117334.7
	(922689.4)	(1100931.1)	(1435615.8)	(1100580.6)	(985100.7)	(1021568.3)
Unexpected Stars	1105101.6***	1744591.8	1710230.3***	598792.6**	582975.9**	610990.1**
	(371108.2)	(1114123.8)	(609148.3)	(273821.4)	(259170.2)	(281788.8)
Stars_{t-1}	768413.4*	1443313.9*	2117296.5***	463260.7**	481265.2**	631606.8***
	(410486.8)	(793151.1)	(619475.5)	(206689.1)	(197573.7)	(222658.0)
Stars_{t-2}	562101.1	-272997.7	122207.5	4177.3	130089.2	155496.2
	(412305.3)	(637024.6)	(500808.9)	(191223.5)	(215417.6)	(228011.4)
Wins_{t-1}	-32711.4	3947.3	-65568.7	18878.6	10558.2	2806.8
	(105049.4)	(96470.6)	(101804.2)	(103449.3)	(102256.7)	(101503.3)
Wins_{t-2}	41883.4	104381.9*	85021.8	94179.9	77280.7	74368.0
	(56659.1)	(61508.8)	(61971.4)	(65550.6)	(67989.5)	(65025.5)
CoachCareer_{t-1}	2590453.4	1959475.8	2491360.8	1370681.5	1347287.4	1466239.9
	(2063239.9)	(2062362.3)	(2079642.2)	(2052005.7)	(2057270.6)	(2071838.5)
BowlGame_{t-1}	859515.7*	702657.6	807492.9*	619397.3	639135.4	625602.6
	(462473.7)	(444804.2)	(455981.4)	(457832.0)	(452720.1)	(451378.9)
BowlWin_{t-1}	-382303.9	-234871.3	-185765.7	-384303.1	-397112.6	-391574.2
	(420180.1)	(427313.7)	(403261.7)	(422752.6)	(426789.8)	(427719.2)
Distance	-25887.2	-26121.9	-25630.8	-21458.9	-21585.4	-22095.6
	(16511.1)	(17388.0)	(17055.4)	(17326.9)	(17406.1)	(17307.2)
PerCapPI	177110.4	246154.4	270217.5	220570.6	215235.2	207043.5
	(317008.1)	(332009.2)	(321752.5)	(327971.9)	(327810.2)	(322773.5)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.774	0.775	0.779	0.774	0.774	0.774
Adjusted R^2	0.972	0.972	0.972	0.972	0.972	0.972
F-Stat	3.155	1.592	0.0847	0.743	0.799	0.257
P-Value	0.0787	0.210	0.772	0.391	0.373	0.613

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28

Marginal Revenue Product of Expected and Unexpected Star College Basketball Players. This table reports fixed effects estimates of the marginal revenue products of expected and unexpected star basketball players from Model (2.1) over the sample period 2005-2012. Star players are measured according to one of eight ex-post performance metrics: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The number of star players on a team are then decomposed into "expected" and "unexpected" star players. Expected stars are those who are stars as measured by ex-post performance who were also a Five Star Rivals.com recruit. Unexpected stars are those who are stars as measured by ex-post performance who were not rated as a Five Star Rivals.com recruit. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. The full estimation results are reported in Table 54 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Stars	1861841.5**	464789.8*	329225.9	180444.1	179831.3	306729.6	351755.1	998639.6***
	(865063.9)	(273430.6)	(249630.0)	(127554.4)	(172113.0)	(186153.0)	(371360.9)	(342904.8)
Unexpected Stars	333899.7	776734.2**	352397.1	216737.3**	714362.0*	495444.7*	305419.4	238009.9*
	(738243.7)	(316859.4)	(255635.8)	(105786.4)	(412900.4)	(298607.7)	(197988.3)	(129040.5)
Stars_{t-1}	134905.6	24465.2	89835.5	-10156.3	203925.4	1087.7	14305.8	29458.2
	(400322.9)	(293195.0)	(179641.7)	(88102.8)	(299590.9)	(231498.6)	(103486.1)	(81657.1)
Stars_{t-2}	207972.0	156328.3	207951.5	224509.8**	248992.5	104352.5	174122.5	84942.4
	(326755.0)	(215013.3)	(157744.2)	(100878.3)	(245767.6)	(201283.0)	(113355.3)	(83915.0)
Wins_{t-1}	5543.7	4694.5	4810.1	6687.5	5017.2	5243.2	5527.5	4591.3
	(4770.4)	(4672.1)	(4707.3)	(4630.3)	(4578.1)	(4611.1)	(4769.1)	(4853.3)
Wins_{t-2}	11622.1***	10809.6**	10366.6**	7456.1	10949.4***	11040.6***	10884.9**	11263.5**
	(4338.1)	(4405.4)	(4409.5)	(4627.5)	(3914.1)	(4097.3)	(4496.4)	(4571.0)
$\text{CoachCarTourn}_{t-1}$	53172.9***	53859.3***	52980.5***	53234.5***	53647.5***	54757.7***	54038.6***	49759.6***
	(16315.8)	(16450.1)	(16460.1)	(16410.5)	(16279.7)	(16333.9)	(16408.0)	(16567.3)
NCAATourn_{t-1}	173884.1**	167026.7**	164312.6**	170068.9**	161540.0**	158358.8**	160024.8**	165053.1**
	(76207.2)	(74672.9)	(75261.0)	(77372.7)	(73351.3)	(74985.9)	(75034.4)	(75412.5)
Champ_{t-1}	2011876.3**	1848919.8***	1898268.1***	2030169.0***	1756136.6**	1748700.6**	1826897.4***	2001601.0***
	(983545.1)	(546635.7)	(647804.9)	(640066.7)	(773877.7)	(742747.4)	(610354.7)	(650977.6)
Distance	-1028.5	-969.5	-1074.7	-1296.0	-1257.8	-1186.8	-1387.3	-1145.0
	(1511.8)	(1557.6)	(1543.0)	(1572.4)	(1588.1)	(1552.1)	(1547.5)	(1529.8)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.671	0.670	0.668	0.672	0.668	0.669	0.668	0.670
Adjusted R^2	0.969	0.968	0.968	0.969	0.968	0.968	0.968	0.968
F-Stat	1.560	0.431	0.00326	0.0594	1.476	0.369	0.0122	5.967
P-Value	0.213	0.512	0.954	0.808	0.225	0.544	0.912	0.0152

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29

Injured Star Players

This table reports the number of star players that had season ending injuries or suspensions in the data over the sample periods 2000-2012 and 2003-2012. Injuries or suspensions are deemed to be “season ending” if they caused a player to miss the last half of the season (or more). Injured or suspended stars are those that were designated stars in year t and suffered a season ending injury in year $t+1$ (or in the offseason if they took a medical redshirt in year $t+1$).

	Number of Injuries	
Football Star Measure	2000-2012	2003-2012
(1) All-Americans	3	3
(2) Heisman Finalists	1	1
(3) Heisman Nominees	2	2
(4) Top 10 TDs or YDs	12	8
(5) Top 10 TDs or YDs or PER	12	8
(6) Top 10 TDs or YDs (Top 10 QB by PER only)	12	8
	Number of Injuries	
Basketball Star Measure	2000-2012	2003-2012
(1) Award Winners	0	0
(2) All American First Team	0	0
(3) All Americans	0	0
(4) NBA Drafted	0	0
(5) NBA Top 5 Draft Pick	0	0
(6) NBA Top 10 Draft Pick	0	0
(7) Top 10 Points Scorers	2	1
(8) Top 20 Points Scorers	3	1

Table 30

Marginal Revenue Product of Star College Football Players. This table reports instrumental variable estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The F-statistics and corresponding p-values from the first stage regression are reported at the bottom of the table. The first stage estimation and full estimation results are reported in Tables 55 and 56 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	3352048.8*	31016231.2	4461936.1	-325897.0	-451761.8	-638610.6
	(2029944.2)	(63869507.7)	(4631794.7)	(1761384.2)	(1925194.5)	(3548987.3)
Stars_{t-1}	1145799.4**	4683159.5	2482640.5***	336907.6	315453.9	374615.7
	(449170.6)	(7042909.1)	(774044.5)	(307185.4)	(356973.7)	(740135.0)
Stars_{t-2}	939580.0**	5721367.3	719271.2	-182067.4	-72906.5	-115251.2
	(466323.3)	(13159114.6)	(1104045.3)	(392099.1)	(414365.1)	(786394.5)
Wins_{t-1}	-84306.6	-178687.0	-89140.2	47064.3	43107.9	40095.6
	(107624.2)	(440717.8)	(102550.1)	(106177.7)	(109552.0)	(139836.1)
Wins_{t-2}	65369.0	143180.8	82589.2	100274.1	85756.2	85903.6
	(66246.3)	(154561.8)	(64187.3)	(67170.6)	(68894.9)	(74135.2)
CoachCareer_{t-1}	3085225.6*	4644883.5	2880010.4	1544703.0	1627646.1	1628212.6
	(1709751.7)	(6796621.5)	(1757220.8)	(1694773.6)	(1751238.6)	(1720642.1)
BowlGame_{t-1}	941503.6**	505151.5	769309.4*	554650.7	578689.7	602101.5
	(451919.7)	(962634.1)	(438882.7)	(448386.7)	(445757.8)	(441982.9)
BowlWin_{t-1}	-339821.8	116548.9	-107854.0	-366926.5	-352897.6	-328632.0
	(344562.8)	(1019531.5)	(362519.6)	(336782.8)	(345584.6)	(382430.0)
Distance	-22733.9	-40357.4	-25887.6*	-23063.5	-22641.2	-22712.3
	(14176.4)	(41881.0)	(13796.1)	(14421.4)	(14316.8)	(14327.6)
PerCapPI	169103.1	821280.9	339000.2	195442.0	196669.3	195767.3
	(231400.6)	(1327571.9)	(255842.7)	(232845.0)	(232035.0)	(232387.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.755	0.0766	0.769	0.766	0.764	0.762
FS F-Stat	14.81	0.273	7.944	9.458	7.346	2.607
FS p-value	0.000129	0.602	0.00494	0.00217	0.00687	0.107

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 31

Marginal Revenue Product of Star College Basketball Players. This table reports instrumental variable estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for two different measures of star player are reported: (1) Top 10 Points Scorers and (2) Top 20 Points Scorers. The F-statistics and corresponding p-values from the first stage regression are reported at the bottom of the table. The first stage estimation and full estimation results are reported in Tables 57 and 58 in Appendix A.7.

	(1)		(2)	
	PTS 10		PTS 20	
Stars			-2060650.7	(4712952.1)
Stars_{t-1}	-14324.8	(109625.6)	-341069.3	(742329.6)
Stars_{t-2}	109321.6	(110055.9)	-482453.9	(1119310.9)
Wins_{t-1}	5621.2	(5236.7)	11295.1	(14340.6)
Wins_{t-2}	11545.7***	(4428.7)	20542.6	(19901.9)
$\text{CoachCarTourn}_{t-1}$	54048.2***	(11019.9)	62527.3***	(24077.2)
NCAATourn_{t-1}	164567.1**	(73133.0)	205250.6	(125761.7)
Champ_{t-1}	1802254.2***	(322007.8)	1391137.2	(1020610.9)
Distance	-1348.6	(1768.0)	-1580.6	(2201.1)
Team Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Confr. Fixed Effects	Yes		Yes	
N	2820		2820	
Within R^2	0.667		0.533	
FS F-Stat	.		0.876	
FS p-value	.		0.349	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 32

Marginal Revenue Product of Gaining Versus Losing a Star College Football Player. This table reports first-difference estimates of the marginal revenue product associated with gaining or losing a star football player from Model (2.6) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. F-statistics and corresponding p-values for the null hypothesis that gaining a star and losing a star are statistically equivalent are reported at the bottom of the table. The full estimation results are reported in Tables 59 in Appendix A.7.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
$\Delta \text{Stars}_t \times$GainStars	767259.7*	2591514.5**	1541978.3*	764154.7**	732774.2**	751373.8**
	(409898.9)	(1012532.7)	(822193.9)	(340852.0)	(318469.5)	(349115.1)
$\lvert\Delta \text{Stars}_t\rvert \times$LoseStars	-971939.3*	343956.3	-1333385.4*	-814791.5***	-771677.6***	-747472.0***
	(501617.8)	(1150132.4)	(802480.9)	(265015.4)	(252527.0)	(281734.2)
$\Delta \text{Stars}_{t-1}$	612304.6*	887716.4	2065735.2***	580330.8***	586439.8***	722016.3***
	(346843.1)	(900151.3)	(757039.8)	(205986.1)	(208918.3)	(217054.1)
$\Delta \text{Stars}_{t-2}$	213627.3	-364581.0	213379.7	-40878.9	90550.3	227177.4
	(354136.4)	(755705.8)	(548891.4)	(172334.5)	(189095.0)	(207782.0)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	936	936	936	936	936	936
R^2	0.145	0.160	0.169	0.168	0.166	0.162
F-Stat	0.0884	4.703	0.0252	0.0142	0.00972	0.0000817
P-Value	0.767	0.0324	0.874	0.905	0.922	0.993

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33

Marginal Revenue Product of Gaining Versus Losing a Star College Basketball Player. This table reports first-difference estimates of the marginal revenue product associated with gaining or losing a star basketball player from Model (2.6) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. F-statistics and corresponding p-values for the null hypothesis that gaining a star and losing a star are statistically equivalent are reported at the bottom of the table. The full estimation results are reported in Tables 60 in Appendix A.7.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \text{Stars}_t \times \text{GainStars}$	1249401.5**	1022006.2***	385237.4	262206.6**	612977.8**	542524.9**	438588.8	454806.1**
	(567449.1)	(251755.9)	(255794.4)	(114139.3)	(259816.6)	(222327.7)	(273236.2)	(213839.4)
$\lvert\Delta \text{Stars}_t\rvert \times \text{LoseStars}$	-1069510.3*	18293.2	-178812.8	-7130.9	-42078.2	-80122.6	-239836.4	-283733.6*
	(609260.0)	(406132.0)	(226092.5)	(130412.1)	(527181.9)	(242545.4)	(190480.7)	(160232.2)
$\Delta \text{Stars}_{t-1}$	1207782.7***	-21121.5	80006.9	-35134.1	22517.7	59302.2	68989.6	123678.1
	(440837.3)	(216268.1)	(129649.5)	(105900.3)	(397336.2)	(191673.0)	(119312.7)	(109812.7)
$\Delta \text{Stars}_{t-2}$	556357.4	79487.6	3385.2	150899.9	-30961.0	-61833.0	79607.9	73114.6
	(373802.4)	(213477.4)	(156103.7)	(108005.0)	(250395.0)	(201046.3)	(111521.2)	(91096.6)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2819	2819	2819	2819	2819	2819	2819	2819
R^2	0.103	0.101	0.095	0.107	0.096	0.097	0.095	0.101
F-Stat	0.0575	3.149	0.504	2.131	0.707	1.758	0.499	0.558
P-Value	0.811	0.0771	0.478	0.145	0.401	0.186	0.480	0.456

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34

Marginal Revenue Product of Losing a Star College Football Player Due to Injury. This table reports difference-in-difference estimates of the marginal revenue product associated with losing a star football player due to injury from Model (2.5) over the sample period 2000-2012. The control group is defined to be teams that had exactly one star player in year t and exactly one star player in year $t+1$. The treatment goup in Panel A is defined to be teams that had exactly one star player in year t that had a season ending injury in $t+1$ and zero star players in $t+1$. The treatment group in Panel B is defined to be teams that had exactly one star player in year t that had a season ending injury in $t+1$ and zero or one star player in $t+1$. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for three different measures of star player are reported: (1) Top 10 in offensive touchdowns or yards, (2-3) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (1,2,3) is how star Quarterbacks are measured with (2) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (3) is a Top 10 Quarterback in pass efficiency rating alone. The number of treatments are reported at the bottom of each panel in the table.

Panel A

	(1) TDYds	(2) PERTDsYds	(3) TopPER
Lose Star	-1417026.7	-1026420.7	-1029946.9
	(2848835.0)	(2126490.2)	(2023918.2)
Team-Cohort Fixed Effects	Yes	Yes	Yes
Year-Cohort Fixed Effects	Yes	Yes	Yes
N	186	172	160
Treatments	3	3	3
R^2	0.993	0.995	0.996

Panel B

	(1) TDYds	(2) PERTDsYds	(3) TopPER
Lose Star	-1091500.4	-650645.3	-793007.5
	(3030460.0)	(2322512.8)	(2033321.2)
Team-Cohort Fixed Effects	Yes	Yes	Yes
Year-Cohort Fixed Effects	Yes	Yes	Yes
N	190	176	166
Treatments	5	5	6
R^2	0.993	0.995	0.996

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35

Marginal Revenue Product of Losing a Star College Basketball Player Due to Injury. This table reports difference-in-difference estimates of the marginal revenue product associated with losing a star basketball player due to injury from Model (2.5) over the sample period 2000-2012. The control group is defined to be teams that had exactly one star player in year t and exactly one star player in year $t + 1$. The treatment goup in Panel A is defined to be teams that had exactly one star player in year t that had a season ending injury in $t + 1$ and zero star players in $t + 1$. The treatment group in Panel B is defined to be teams that had exactly one star player in year t that had a season ending injury in $t+1$ and zero or one star player in $t+1$. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for two different measures of star player are reported: (1) Top 10 Points Scorers and (2) Top 20 Points Scorers. The number of treatments are reported at the bottom of each panel in the table.

Panel A

	(1) PTS 10	(2) PTS 20
Lose Star	-254948.5***	-194976.8
	(51918.1)	(506034.7)
Team-Cohort Fixed Effects	Yes	Yes
Year-Cohort Fixed Effects	Yes	Yes
N	44	94
Treatments	2	2
R^2	0.996	0.993

Panel B

	(1) PTS 10	(2) PTS 20
Lose Star	-254948.5***	-587166.6
	(51918.1)	(541189.0)
Team-Cohort Fixed Effects	Yes	Yes
Year-Cohort Fixed Effects	Yes	Yes
N	44	96
Treatments	2	3
R^2	0.996	0.993

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 36

Marginal Revenue Product of Star College Basketball Players - Scully Method. This table reports estimates of a star college basketbball player's marginal revenue product using the Scully Method over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. Panel A contains the estimates of the marginal revenue of wins from Equation (2.7), standard errors are in parentheses and have been clustered by team. The full estimation results for the marginal revenue of wins are reported in Table 61 in the appendix. Panel A also contains the marginal product of a star basketball player calculated as the average number of wins contributed by star players across teams and years. Panel B contains the marginal revenue product from the Scully Method, computed by multiplying the marginal revenue by the marginal product. The standard errors for the marginal revenue products are computed using the Delta Method.

	Panel A							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marginal Revenue (Wins)	18451.6***	18451.6***	18451.6***	18451.6***	18451.6***	18451.6***	18451.6***	18451.6***
	(4378.1)	(4378.1)	(4378.1)	(4378.1)	(4378.1)	(4378.1)	(4378.1)	(4378.1)
Marginal Product	8.174	7.478	7.046	5.383	7.021	6.336	6.782	6.347
	Panel B							
Scully Method	150817.7***	137974.9***	130014.4***	99321.2***	129541.2***	116912.2***	125141.5***	117111.2***
	(35785.1)	(32737.9)	(30849.1)	(23566.3)	(30736.8)	(27740.2)	(29692.8)	(27787.4)
N	2820	2820	2820	2820	2820	2820	2820	2820

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

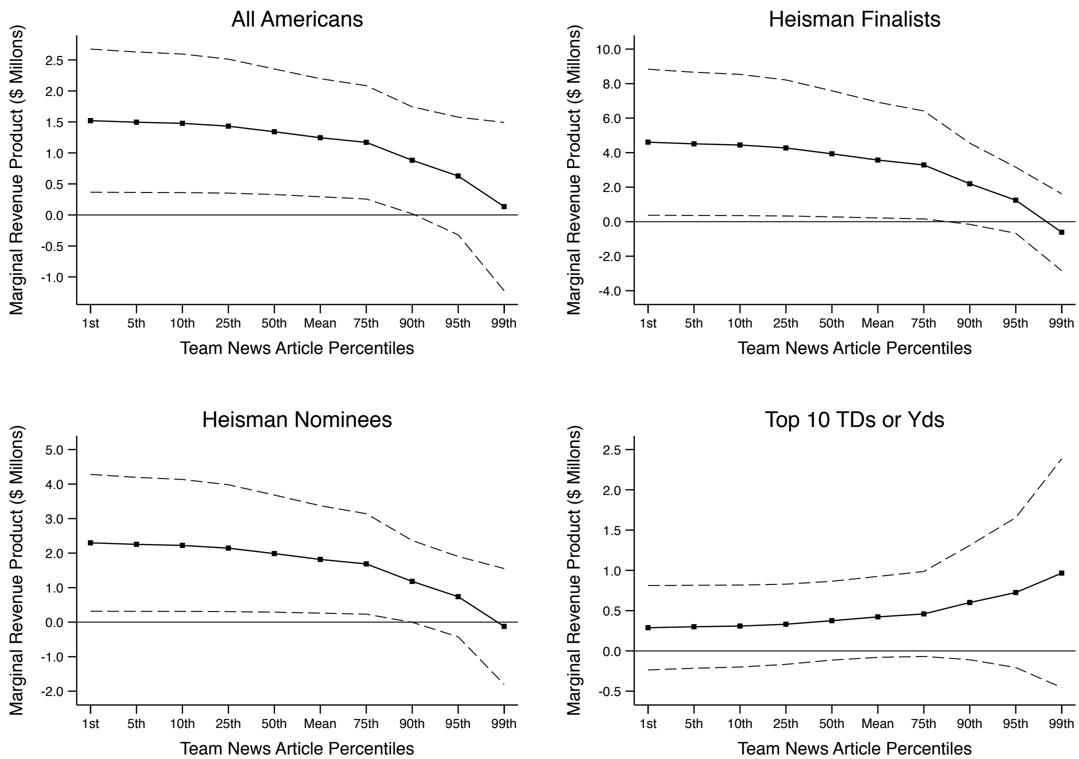

Figure 3

This figure plots the marginal revenue product of star college football players from Model (2.8) for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors bands for the marginal effect are computed using the delta method at the 5% significance level. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The full estimation results used in these figures are reported in Tables 62 and 63 in Appendix A.7.

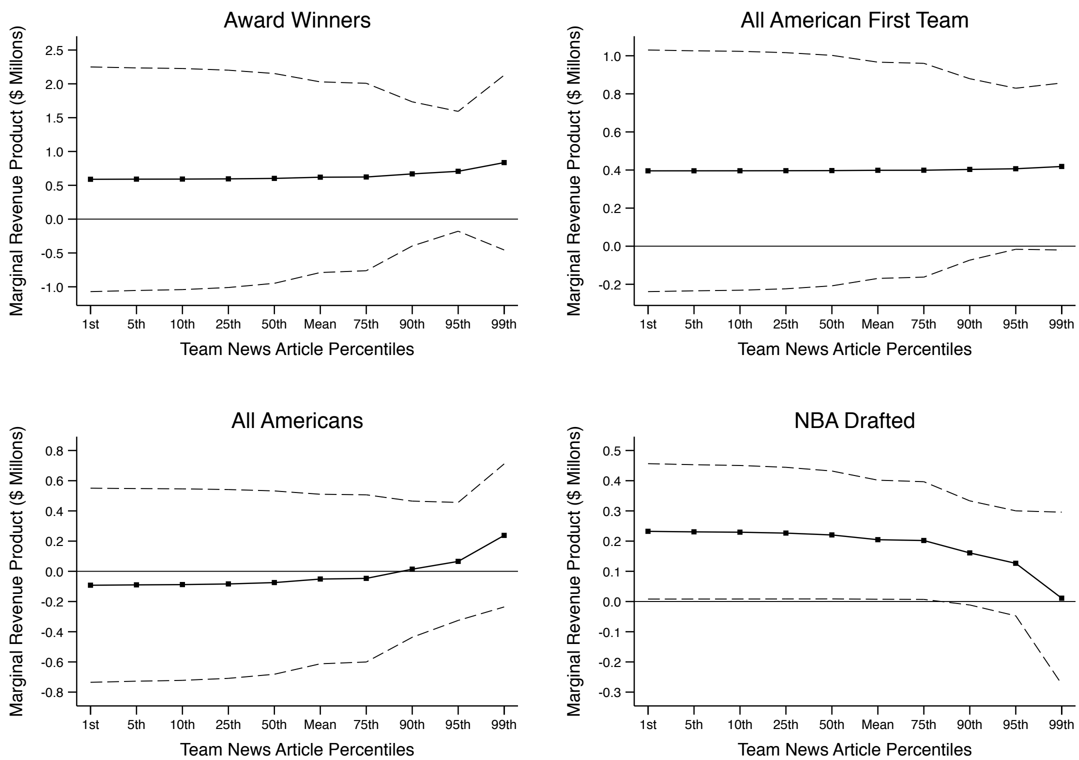

Figure 4

This figure plots the marginal revenue product of star college basketball players from Model (2.8) for various percentiles of media exposure, as measured by the number of media articles mentioning the basketball team, over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors bands for the marginal effect are computed using the delta method at the 5% significance level. Estimates for four different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner, or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, and (4) NBA Drafted Players. The full estimation results used in these figures are reported in Tables 68 and 69 in Appendix A.7.

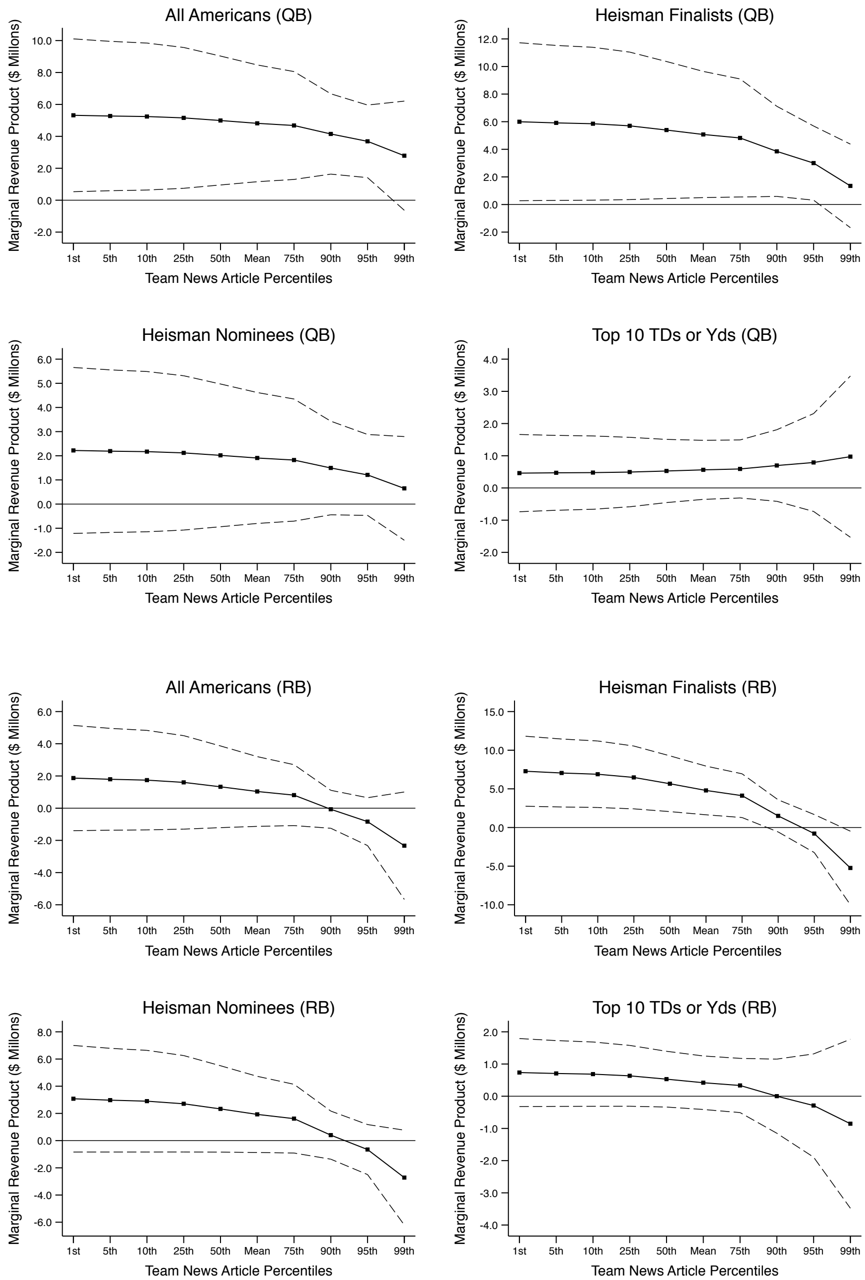

Figure 5

This figure plots the marginal revenue product of star college football Quarterbacks and Running Backs from Model (2.9) for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors bands for the marginal effect are computed using the delta method at the 5% significance level. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The full estimation results used in these figures are reported in Tables 64, 65 and 67 in the Appendix A.7.

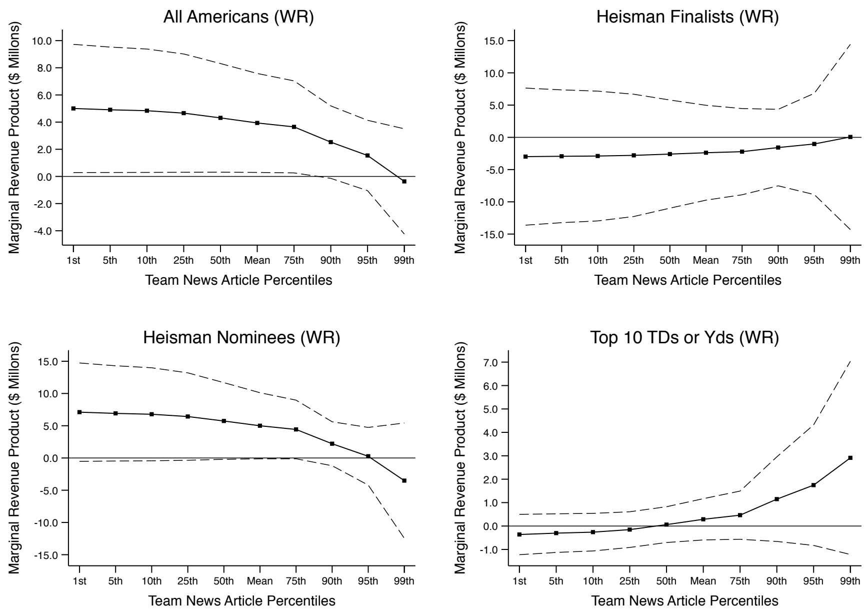

Figure 6

This figure plots the marginal revenue product of star college football Running Backs and Wide Receivers from Model (2.9) for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors bands for the marginal effect are computed using the delta method at the 5% significance level. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The full estimation results used in these figures are reported in Tables 64 and 66 in Appendix A.7.

APPENDIX

A.1 Derivation of the Stochastic Discount Factor

A.1.1 Solving the Representative Agent's Problem

We derive the general form for the stochastic discount factor. Suppose investors have preferences as in Epstein and Zin (1989) where the preference parameters γ_t and ψ_t are allowed to vary over time. Let $\theta_t = \frac{1-\gamma_t}{1-\frac{1}{\psi_t}}$. Then the investor in this economy solves the following portfolio allocation problem

$$V_t(W_t) = \max_{\{C_t,h_t\}} \left[C_t^{\frac{1-\gamma_t}{\theta_t}} + \delta \left(\mathbf{E}_t \left[V_{t+1}(W_{t+1})^{1-\gamma_t} \right] \right)^{\frac{1}{\theta_t}} \right]^{\frac{\theta_t}{1-\gamma_t}} \tag{A.1}$$

s.t.

$$C_t + P_t' h_{t+1} = d_t' h_t + P_t' h_t \equiv W_t \tag{A.2}$$

where P_t refers to a $n \times 1$ vector of asset prices per share at date t that offers a real dividend stream of d_{t+j}, an $n \times 1$ vector with $j = (1, \ldots, \infty)$, and h_t is an $n \times 1$ vector of asset holdings at the end of period $t-1$, which includes the risk-free asset. We can rewrite equation A.2 as

$$(W_t - C_t) R_{a,t+1} = W_{t+1} \tag{A.3}$$

where $W_t - C_t = P_t' h_{t+1}$ is the amount of capital invested in the asset market and

$$R_{a,t+1} = \frac{P_{t+1}' h_{t+1} + d_{t+1}' h_{t+1}}{P_t' h_{t+1}} = \frac{W_{t+1}}{W_t - C_t} \tag{A.4}$$

is the return on the agent's asset portfolio, which in this economy is just the gross return on the asset that pays aggregate consumption as dividend. Given that the value function is homogeneous of degree one in W_t and the linearity of W_{t+1} in (W_t, C_t), we conjecture the solution $V_t = \phi_t W_t$. Using this conjecture and plugging (A.3) into Equation (A.1) gives

$$\phi_t W_t = \max_{\{C_t, h_t\}} \left[C_t^{\frac{1-\gamma_t}{\theta_t}} + \delta (W_t - C_t)^{\frac{1-\gamma_t}{\theta_t}} \left(\mathbf{E}_t \left[(\phi_{t+1} R_{a,t+1})^{1-\gamma_t} \right] \right)^{\frac{1}{\theta_t}} \right]^{\frac{\theta_t}{1-\gamma_t}}.$$

We can decompose the investor's problem into two parts

$$\phi_t W_t = \max_{C_t \in [0, W_t]} \left[C_t^{\frac{1-\gamma_t}{\theta_t}} + \delta \left[(W_t - C_t) \mu^* \right]^{\frac{1-\gamma_t}{\theta_t}} \right]^{\frac{\theta_t}{1-\gamma_t}} \tag{A.5}$$

$$\mu^* = \max_{\mathbf{h}_t \in \mathbb{R}_+^n, h_t \iota' = 1} \left(\mathbf{E}_t \left[(\phi_{t+1} \mathbf{h}_t \mathbf{R}'_{t+1})^{1-\gamma_t} \right] \right)^{\frac{1}{1-\gamma_t}} \tag{A.6}$$

Where $\mathbf{h}_t$ and $\mathbf{R}_{t+1}$ are $1 \times N$ vectors of portfolio weights and returns with ι' a $N \times 1$ column vector of ones. Equation (A.5) is the investor's consumption choice problem, while Equation (A.6) is the investor's portfolio choice problem. We will first solve the investor's consumption problem for an arbitrary μ^* and then use the result to find the solution to the portfolio choice problem. Since Equation (A.5) is homogenous of degree one, we conjecture the following solution to the optimal consumption policy

$$C_t^* = B_t W_t$$

where B_t is the consumption wealth ratio. Using this conjecture in Equation (A.5) gives

$$\phi_t^{\frac{1-\gamma_t}{\theta_t}} = \max_{B_t \in [0,1]} \left[B_t^{\frac{1-\gamma_t}{\theta_t}} + \delta \left[(1 - B_t) \mu^* \right]^{\frac{1-\gamma_t}{\theta_t}} \right] \tag{A.7}$$

The first order condition of this equation yields

$$B_t^{\frac{1-\gamma_t}{\theta_t} - 1} = \delta \left[(1 - B_t) \mu^* \right]^{\frac{1-\gamma_t}{\theta_t} - 1} \mu^* \tag{A.8}$$

Using equations (A.7) and (A.8) we obtain

$$\phi_t = B_t^{\frac{1}{1-\psi_t}}$$

hence

$$\phi_{t+1} = B_{t+1}^{\frac{1}{1-\psi_{t+1}}} \tag{A.9}$$

which is an invertible function of ϕ_{t+1}, which we can use to solve the investor's portfolio choice problem by plugging Equation (A.9) into Equation (A.6) to get

$$\mu^* = \left(\mathbf{E}_t \left[\left(B_{t+1}^{\frac{1}{1-\psi_{t+1}}} R_{a,t+1} \right)^{1-\gamma_t} \right] \right)^{\frac{1}{1-\gamma_t}}$$

where $R_{a,t+1} = \mathbf{h}_t^* \mathbf{R}'_{t+1}$ is the gross return of the optimal portfolio. We can then use this with Equation (A.8) that comes from the optimal consumption decision to get

$$\left(\frac{B_t}{1 - B_t} \right)^{-\frac{1}{\psi_t}} = \delta \left(\mathbf{E}_t \left[\left(B_{t+1}^{\frac{1}{1-\psi_{t+1}}} R_{a,t+1} \right)^{1-\gamma_t} \right] \right)^{\frac{1}{\theta_t}}$$

Rearranging this expression gives the following Euler equation

$$1 = \delta^{\theta_t} \mathbf{E}_t \left[\left(\frac{B_t}{1 - B_t} \right)^{\frac{\theta_t}{\psi_t}} B_{t+1}^{\frac{1-\gamma_t}{1-\psi_{t+1}}} R_{a,t+1}^{1-\gamma_t} \right] \tag{A.10}$$

From the budget constraint (A.3) and the fact that $C_t = B_t W_t$, we know

$$\frac{B_t}{1 - B_t} = \frac{C_t}{W_t} \frac{W_t}{(W_t - C_t)} = \frac{C_t}{W_{t+1}} R_{a,t+1} = \frac{C_t}{C_{t+1}} \frac{C_{t+1}}{W_{t+1}} R_{a,t+1} = B_{t+1} \frac{R_{a,t+1}}{G_{t+1}}$$

plugging this into Equation (A.10) and rearranging gives

$$
\begin{aligned}
1 &= \delta^{\theta_t}\mathbf{E}_t\left[\left(B_{t+1}\frac{R_{a,t+1}}{G_{t+1}}\right)^{\frac{\theta_t}{\psi_t}} B_{t+1}^{\frac{1-\gamma_t}{1-\psi_{t+1}}} R_{a,t+1}^{1-\gamma_t}\right] \\
1 &= \delta^{\theta_t}\mathbf{E}_t\left[G_{t+1}^{-\frac{\theta_t}{\psi_t}} B_{t+1}^{\frac{\theta_t}{\psi_t}+\frac{1-\gamma_t}{1-\psi_{t+1}}} R_{a,t+1}^{\frac{\theta_t}{\psi_t}+1-\gamma_t}\right]
\end{aligned}
\tag{A.11}
$$

Let $\xi_{t,t+1} \equiv \theta_t - \frac{1-\gamma_t}{1-\frac{1}{\psi_{t+1}}}$ and notice that

$$
\frac{\theta_t}{\psi_t} + 1 - \gamma_t = \frac{1-\gamma_t}{\psi_t - 1} + (1-\gamma_t) = \frac{(1-\gamma_t)(1+\psi_t-1)}{\psi_t-1} = \frac{(1-\gamma_t)\psi_t}{\psi_t - 1} = \theta_t
$$

and after a few algebraic manipulations, it can be shown that

$$
\frac{\theta_t}{\psi_t} + \frac{1-\gamma_t}{1-\psi_{t+1}} = \theta_t - \frac{1-\gamma_t}{1-\frac{1}{\psi_{t+1}}} = \xi_{t,t+1}
$$

So the Equation (A.11) becomes

$$
\mathbf{E}_t\left[\delta^{\theta_t} G_{t+1}^{-\frac{\theta_t}{\psi_t}} B_{t+1}^{\xi_{t,t+1}} R_{a,t+1}^{\theta_t}\right] = 1
$$

Factoring out a $R_{a,t+1}$ then gives

$$
\mathbf{E}_t\left[\delta^{\theta_t} G_{t+1}^{-\frac{\theta_t}{\psi_t}} B_{t+1}^{\xi_{t,t+1}} R_{a,t+1}^{\theta_t-1} R_{a,t+1}\right] = 1
$$

Hence, the general form for the stochastic discount factor is given by

$$
M_{t+1} = \delta^{\theta_t} G_{t+1}^{-\frac{\theta_t}{\psi_t}} B_{t+1}^{\xi_{t,t+1}} R_{a,t+1}^{-(1-\theta_t)} \tag{A.12}
$$

Notice that when time variation in the preference parameters is shut down so that $\gamma_t = \gamma$ and $\psi_t = \psi$ for all t we have $\xi_{t,t+1} = 0$ and this stochastic discount factor collapses to the usual one under standard Epstein and Zin (1989) preferences.

A.1.2 Equilibrium Stochastic Discount Factor and Pricing Equations

Note that Equation (A.12) is derived only from information about the agent's preferences and budget constraint. Given the assumed Lucas endowment economy, we know there is a single non-durable consumption good C_t with total supply given by the process $C = \{C_t\}$. Equity in this economy is simply a claim to the endowment process and is the only asset held in non-zero net supply. Let this asset be the first element in vector P_t' above and normalize the number of shares in this economy to 1. Hence, the equilibrium in this economy is the price process $P = \{P_t\}$ and consumption allocation C such that the goods market and asset market clears. Specifically, the P such that $C_t = d_t' e_1$ and $h_t' = e_1$ for $t \geq 1$ where $e_1 = (1, 0, \ldots, 0)'$.

Let $P_{k,t}$ and $D_{k,t}$ be the price and dividend (respectively) of asset k. Define the dividend growth rate of asset k as $\lambda_{k,t+1} = \frac{D_{k,t+1}}{D_{k,t}}$. Lastly, let $Z_{k,t} = \frac{P_{k,t}}{D_{k,t}}$ be the price dividend ratio of asset k. Notice that in the Lucas endowment economy, in equilibrium the budget constraint (A.2) reduces to $W_t = C_t + P_t$, hence

$$B_t = \frac{C_t}{W_t} = \frac{C_t}{C_t + P_t} = \frac{1}{1 + \frac{P_t}{C_t}} = \frac{1}{1 + Z_{a,t}} \tag{A.13}$$

The gross return of asset k, is given by

$$R_{k,t+1} = \frac{P_{k,t+1} + D_{k,t+1}}{P_{k,t}} = \frac{Z_{k,t+1} + 1}{Z_{k,t}} \lambda_{k,t+1}. \tag{A.14}$$

We can now use Equations (A.13) and (A.14) along with Equation (A.12) to derive an expression for the SDF in equilibrium:

$$M_{t+1} = \delta^{\theta_t} Z_{a,t}^{1-\theta_t} G_{t+1}^{-\gamma_t} (Z_{a,t+1} + 1)^{\zeta_{t,t+1} - 1} \tag{A.15}$$

where $\zeta_{t,t+1} = \frac{1-\gamma_t}{1-\frac{1}{\psi_{t+1}}}$. Given this expression for the SDF, in equilibrium, we have the following Euler equation

$$\mathbf{E}_t\left[M_{t+1}R_{k,t+1}\right] = 1 \tag{A.16}$$

which is the pricing equation for any arbitrary asset k with gross return $R_{k,t+1}$. We can now derive expressions for the price-dividend ratio and excess returns for an arbitrary asset k as well as the risk-free rate in terms of observables. Substituting equations (A.14) and (A.15) into Equation (A.16), and keeping in mind that $\zeta_{t,t+1}$ is a non-linear function of expressions not in the information set at time t, gives

$$Z_{k,t} = \delta^{\theta_t} Z_{a,t}^{1-\theta_t}\mathbf{E}_t\left[G_{t+1}^{-\gamma_t}(Z_{a,t+1}+1)^{\zeta_{t,t+1}-1}(Z_{k,t+1}+1)\lambda_{k,t+1}\right] \tag{A.17}$$

which gives us an expression for the price-dividend ratio of any arbitrary asset k. Using the Euler equation along with Equation (A.14) and the formula for covariance, it can be shown that the conditional risk-free gross return satisfies

$$\mathbf{E}_t[R_{f,t+1}] = \frac{1}{\mathbf{E}_t[M_{t+1}]} \tag{A.18}$$

and the conditional excess return on asset k satisfies the following expression

$$\mathbf{E}_t[R_{k,t+1} - R_{f,t+1}] = Z_{k,t}^{-1}\mathbf{E}_t\left[(Z_{k,t+1}+1)\lambda_{k,t+1}\right] - \left(\mathbf{E}_t[M_{t+1}]\right)^{-1} \tag{A.19}$$

Equations (A.17)-(A.19) allow us to compute price-dividend ratios, as well as moments for the risk-free rate and equity premium in terms of observables.

A.2 Equivalent Representation of the Equilibrium SDF

This appendix shows how the equilibrium stochastic discount factor implied by the model can be equivalently expressed as a function of prices multiplied by the usual stochastic discount factor under standard Epstein and Zin (1989) preferences where the parameters are allow to be time varying. Recall the definitions of

$$\theta_t = \frac{1-\gamma_t}{1-\frac{1}{\psi_t}}$$
$$\zeta_{t,t+j} = \frac{1-\gamma_t}{1-\frac{1}{\psi_{t+1}}}.$$

The equilibrium stochastic discount factor derived in Equation (A.15) can be written as

$$\begin{aligned}
M_{t+1} &= \delta^{\theta_t} Z_{a,t}^{1-\theta_t} G_{t+1}^{-\gamma_t} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-1} \\
&= \delta^{\theta_t} Z_{a,t}^{1-\theta_t} G_{t+1}^{-\gamma_t} (Z_{a,t+1}+1)^{\theta_t-1+\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} Z_{a,t}^{1-\theta_t} G_{t+1}^{-\gamma_t} (Z_{a,t+1}+1)^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{-\gamma_t} \left(\frac{Z_{a,t+1}+1}{Z_{a,t}}\right)^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{1-\gamma_t-\theta_t} \left(\frac{Z_{a,t+1}+1}{Z_{a,t}} G_{t+1}\right)^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{1-\gamma_t-\theta_t} R_{a,t+1}^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{(1-\gamma_t)(1-\frac{1}{1-\frac{1}{\psi_t}})} R_{a,t+1}^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{(1-\gamma_t)(\frac{-\frac{1}{\psi_t}}{1-\frac{1}{\psi_t}})} R_{a,t+1}^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= \delta^{\theta_t} G_{t+1}^{-\frac{\theta_t}{\psi_t}} R_{a,t+1}^{\theta_t-1} (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t} \\
&= M_{t+1}^{ez}(\gamma_t, \psi_t) \cdot (Z_{a,t+1}+1)^{\zeta_{t,t+1}-\theta_t}
\end{aligned}$$

Where $M_{t+1}^{ez}(\gamma_t, \psi_t)$ is the equilibrium stochastic discount factor under the standard Epstein and Zin (1989) preferences where the parameters γ and ψ are allowed to vary over time.

A.3 Data

In this appendix we give a detailed description of the data used in calibrating the model.

A.3.1 Macroeconomy Variables

Real Consumption Growth

The data for real per capita chained (2009) consumption for 1929-2013 comes from the Bureau of Economic Analysis, NIPA Table 7.1. The real consumption per capita level is is computed by adding real expenditures on non-durable goods and services (Table 7.1, lines 16 and 17). All level series are converted to logs and first differences are taken to compute growth rates.

Inflation Rate

The annual CPI for all urban consumers (NSA) for 1925-2013 is taken from the Bureau of Labor Statistics. Inflation rates are calculated by taking log differences of the price indices.

A.3.2 Financial Market Variables

Interest Rates

The annual risk free rate from 1920-2013 is taken from the Global Financial Database at https://www.globalfinancialdata.com/platform/Welcome.aspx. Specifically, we use the yield on 90 day U.S. Government Treasury Bills with ticker symbol ITUSA3D. These nominal rates are converted to real risk free rates by subtracting the inflation rate as calculated above.

Aggregate Stock Returns, Dividends and Price-Dividend Ratio

Value-weighted returns on the S&P 500 stock index from January 1926-December 2013 not including dividends (VWRETX) and including dividends (VWRETD) are obtained from the monthly CRSP update. The series VWRETX and VWRETD are used to compute annual market returns, price-dividend ratios and dividend yields as follows.

Given the *monthly* data series

$$(1 + VWRETX_t) = \frac{P_{t+1}}{P_t}$$
$$(1 + VWRETD_t) = \frac{P_{t+1} + D_{t+1}}{P_t}$$

We initialize $P_0 = 1$ and recursively update $P_t = P_{t-1}(1 + VWRETX_t)$ to construct the market price series. To aggregate up to annual data, for year t we take the sum of dividend levels from January until December over the corresponding year

$$D_t = \sum_{s=0}^{11} D_{t-s} \quad \text{for} \quad t > s$$

Then the annual market return for year t is just the price as of December 31^{st} plus the annual dividend, divided by the price level as of December 31^{st} of the previous year. That is

$$R_{m,t} = \frac{P_t + D_t}{P_{t-12}}$$

Similarly, dividend growth rates and price-dividend ratios are calculated by

$$Gd_t = \frac{D_t}{D_{t-1}} - 1$$
$$PD_t = \frac{P_t}{D_t}.$$

A.4 Numerical Solution Method

In this appendix, we outline the steps to implement and exactly solve the model numerically. Given the discrete state space $S = \{s_1, s_2, s_3, s_4, s_5\}$

- Obtain values for the consumption and dividend growth parameters

$$\{\mu_C, \quad \sigma, \quad \rho, \quad \mu_D, \quad \phi_D\}$$

  from the sample moments in Table 1 of the data. Then set values for consumption and dividend growth states $i \in S$ according to

$$\begin{aligned} g_h &= \mu_C + \sigma \\ g_l &= \mu_C - \sigma \end{aligned}$$

$$\begin{aligned} G(s_1) &= g_h \\ G(i) &= g_l \quad \text{for} \quad i \in \{s_2, s_3, s_4, s_5\} \\ \lambda_D(i) &= \mu_D + \phi_D(G(i) - \mu_C) \quad \text{for} \quad i \in S \end{aligned}$$

- Given values for

$$\{\gamma_0, \quad \gamma_{\text{elev}}, \quad \psi_0, \quad \psi_{\text{depr}}\}$$

set the values for risk aversion and the EIS parameter in states $i \in S$ according to

$$\begin{aligned}
\gamma(i) &= \gamma_0 \quad \text{for} \quad i \in \{s_1, s_2, s_4\} \\
\gamma(i) &= \gamma_{\text{elev}} \quad \text{for} \quad i \in \{s_3, s_5\} \\
\theta(i) &= \frac{1-\gamma(i)}{1-\frac{1}{\psi(i)}} \quad \text{for} \quad i \in S \\
\zeta(i,j) &= \frac{1-\gamma(i)}{1-\frac{1}{\psi(j)}} \quad \text{for} \quad i,j \in S
\end{aligned}$$

- Choose a value for b_{elev}, which is the conditional probability of transitioning from a high to low growth state where risk aversion is elevated. Also, choose a value for and b_{depr}, which is the conditional probability of transitioning from a high to low growth state where the EIS parameter is depressed. Use these values and ρ to calculate the transition matrix

$$\Pi = \begin{bmatrix}
\frac{1+\rho}{2} & [1-(b(1-d)+d)]\left(\frac{1-\rho}{2}\right) & b(1-d)\left(\frac{1-\rho}{2}\right) & d(1-b)\left(\frac{1-\rho}{2}\right) & bd\left(\frac{1-\rho}{2}\right) \\
\frac{1-\rho}{2} & [1-(b(1-d)+d)]\left(\frac{1+\rho}{2}\right) & b(1-d)\left(\frac{1+\rho}{2}\right) & d(1-b)\left(\frac{1+\rho}{2}\right) & bd\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & (1-d)\left(\frac{1+\rho}{2}\right) & 0 & d\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & 0 & (1-b)\left(\frac{1+\rho}{2}\right) & b\left(\frac{1+\rho}{2}\right) \\
\frac{1-\rho}{2} & 0 & 0 & 0 & \left(\frac{1+\rho}{2}\right)
\end{bmatrix}$$

and steady state probabilities

$$\pi = \begin{bmatrix} \frac{1}{2} \\ \\ \frac{(1-b)(1-d)(1-\rho)}{2[(1-\rho)+(1+\rho)(b(1-d)+d)]} \\ \\ \frac{b(1-d)(1-\rho)}{2[1+d-\rho(1-d)][(1-\rho)+(1+\rho)(b(1-d)+d)]} \\ \\ \frac{d(1-b)(1-\rho)}{2[1+b-\rho(1-b)][(1-\rho)+(1+\rho)(b(1-d)+d)]} \\ \\ \frac{d}{1+d-\rho(1-d)} - \frac{d(1-b)(1-\rho)}{2[1+b-\rho(1-b)][(1-\rho)+(1+\rho)(b(1-d)+d)]} \end{bmatrix}$$

where $b = b_{\text{elev}}$ and $d = b_{\text{depr}}$ are written to save space.

- Solve the following system of nonlinear equations for the price-dividend ratio associated with the asset that pays consumption as dividend given by Equation A.17

$$Z_a(i) = \delta \left[\sum_j \Pi(i,j) G(j)^{1-\gamma(i)} (Z_a(j)+1)^{\zeta(i,j)} \right]^{\frac{1}{\theta(i)}} \qquad i \in S, \tag{A.20}$$

The values of $\{Z_a(i)\}_{i \in \mathcal{S}}$ can be computed numerically from these equations via fixed-point methods. However, care must be taken in numerical computations to effectively check a proposed solution $\{Z_a(i)^*\}_{i \in \mathcal{S}}$ since the above expression involves the sum of potentially numerically large quantities (with potentially large exponents) that may encounter the limits of machine precision. Note that the term inside the brackets can be expressed equivalently as

$$\sum_j \Pi(i,j) G(j)^{1-\gamma(i)} (Z_a(j)+1)^{\zeta(i,j)} = \sum_j \Pi(i,j) e^{(1-\gamma(i)) \ln G(j) + \zeta(i,j) \ln(Z_a(j)+1)}.$$

Let

$$Z_{\max}(i) := \max_j \{(1-\gamma(i)) \ln G(j) + \zeta(i,j) \ln(Z_a(j)+1)\},$$

such that

$$Z_a(i) = \delta e^{\frac{Z_{\max}(i)}{\theta(i)}} \left[\sum_j \Pi(i,j) e^{[(1-\gamma(i)) \ln G(j) + \zeta(i,j) \ln(Z_a(j)+1) - Z_{\max}(i)]} \right]^{\frac{1}{\theta(i)}}.$$

Then, the largest exponent inside the sum is always 1, which ensures that the sum can always be stably computed for any candidate solution. Extremely small components of the sum (those with small exponents) can potentially reach minimum machine precision and become effectively numerically zero. However, the potential associated approximation error will then be below any positive numerical tolerance that is selected for evaluating convergence of a given fixed-point method. Then exponentiate to derive the final result.

- Compute the discrete state SDF

$$M(i,j) = \delta^{\theta(i)} G(j)^{-\gamma(i)} \left[\frac{Z_a(j)+1}{Z_a(i)} \right]^{\theta(i)-1} \qquad i,j \in S, \tag{A.21}$$

and for the same reasons as given above, to compute stably, we make the following transformation and compute the exponent in the equivalent expression,

$$M(i,j) = e^{[\theta(i) \ln \delta + (1-\theta(i)) \ln Z_a(i) - \gamma(i) \ln G(j) + (\zeta(i,j)-1) \ln(Z_a(j)+1)]},$$

and then exponentiate to compute the final result.

- Use equations (A.17) and (A.21) to solve the following system of linear equations for the price-dividend ratio associated with the levered consumption asset (market portfolio)

$$Z_m(i) = \sum_j \Pi(i,j) M(i,j) (Z_m(j)+1) \lambda_m(j) \quad i \in S,$$

- Compute the conditional gross return on the risk free asset

$$R_f(i) = \left[\sum_j \Pi(i,j)M(i,j)\right]^{-1} \quad i \in S,$$

and then compute the conditional gross return on the market porfolio

$$R_m(i) = [Z_m(i)]^{-1}\sum_j \Pi(i,j)(Z_m(j)+1)\lambda_m(j) \quad i \in S,$$

From the equations computed in this section,all model implied moments reported in the paper are straightforward to compute.

A.5 Procyclical Elasticity of Intertemporal Substitution

In this appendix, we formally prove the following Lemma

Lemma. *If the discrete state, joint Markov process of $s_t = (G_t, \gamma_t, \psi_t)$ is restricted over states $S = \{s_1, s_2, s_3, s_4, s_5\}$ so that preferences do not revert from irregular (γ_{elev} or ψ_{depr}) to regular (γ_0 or ψ_0) states until high consumption growth is realized, then pro-cyclicality of the EIS parameter ψ_t implies that the $EIS_{t,t+1}$*

$$EIS_{t,t+1} = \frac{1 + M_{t+1}G_{t+1}}{\frac{1}{\psi_t}(1 + M_{t+1}G_{t+1}) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} \tag{A.22}$$

is pro-cyclical where M_{t+1} is the stochastic discount factor and $G_{t+1} = \frac{C_{t+1}}{C_t}$ is aggregate consumption growth.

Proof. Assume that the EIS parameter ψ_t is pro-cyclical in the sense that ψ_t tends to be large when $G_t > G_{t-1}$ and tends to be small when $G_t < G_{t-1}$. Let $s_t = (G_t, \gamma_t, \psi_t)$ be the joint state of consumption growth G_t, risk aversion γ_t and the EIS parameter ψ_t at time t. Denote the set of all potential realizations of state s_t by $\tilde{S}$ so that the pair $\{\tilde{s}_{t-1}, \tilde{s}_t\}$ defines a particular transition path between two arbitrary adjacent periods of the joint Markov process from time $t-1$ to t. Define the sets of transition paths

$$\mathcal{S}_t = \{\{s_{t-1}, s_t\} : \psi_{t-1} = \psi_t, \quad \forall t\}$$
$$\Delta_t = \{\{s_{t-1}, s_t\} : \psi_{t-1} \neq \psi_t, \quad \forall t\}$$

Where $\mathcal{S}_t$ is the set of transition paths at time t such that the EIS parameter is constant and Δ_t is that set of transition paths at time t such that the EIS parameter is time varying. Furthermore, define the following subsets of $\mathcal{S}_t$

$$\mathcal{S}_t^u = \{\{s_{t-1}, s_t\} : \psi_{t-1} = \psi_t \;\text{ and }\; G_{t-1} < G_t, \quad \forall t\}$$
$$\mathcal{S}_t^m = \{\{s_{t-1}, s_t\} : \psi_{t-1} = \psi_t \;\text{ and }\; G_{t-1} = G_t, \quad \forall t\}$$
$$\mathcal{S}_t^d = \{\{s_{t-1}, s_t\} : \psi_{t-1} = \psi_t \;\text{ and }\; G_{t-1} > G_t, \quad \forall t\}$$

and the following subsets of Δ_t

$$\Delta_t^u = \{\{s_{t-1}, s_t\} : \psi_{t-1} \neq \psi_t \;\text{ and }\; G_{t-1} < G_t, \quad \forall t\}$$
$$\Delta_t^m = \{\{s_{t-1}, s_t\} : \psi_{t-1} \neq \psi_t \;\text{ and }\; G_{t-1} = G_t, \quad \forall t\}$$
$$\Delta_t^d = \{\{s_{t-1}, s_t\} : \psi_{t-1} \neq \psi_t \;\text{ and }\; G_{t-1} > G_t, \quad \forall t\}$$

Let the notation $\{\tilde{x}, \tilde{y}\} \in A \rightarrow \{z, w\} \in B$ denote the realization of states $\{\tilde{x}, \tilde{y}\} \in A$ transitioning to *any* state $\{z, w\} \in B$. Given the model setup, there are sixteen cases to check to ensure that all possible transitions paths for the state variable are considered:

Case 1: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t \rightarrow \{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$

In this case, the EIS parameter never changes, $\psi_{t-1} = \psi_t = \psi_{t+1} = \psi$ and Equation (A.22) gives

$$EIS_{t-1,t} = EIS_{t,t+1} = \psi$$

So the cyclicality of the EIS is moot.

Case 2: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t \rightarrow \{s_t, s_{t+1}\} \in \Delta^d_{t+1}$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t$. So the EIS at time $t-1$ is

$$EIS_{t-1,t} = \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right) + \left(\frac{1}{\psi_t} - \frac{1}{\psi_{t-1}}\right)}$$

However, since the EIS parameter did not change $\psi_{t-1} = \psi_t$ we know $EIS_{t-1,t} = \psi_t$. Now, suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta^d_{t+1}$. Given the equation for the EIS

$$EIS_{t,t+1} = \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t,t+1}G_{t+1}\right) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)}$$

but since $G_t > G_{t+1}$ and by the pro-cyclicality of ψ_t it follows that $\psi_{t+1} < \psi_t$ and hence $\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right) > 0$ so that

$$\begin{aligned}
EIS_{t,t+1} &= \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t,t+1}G_{t+1}\right) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} \\
\frac{EIS_{t,t+1}}{EIS_{t-1,t}} &= \frac{1 + M_{t,t+1}G_{t+1}}{\left(1 + M_{t,t+1}G_{t+1}\right) + EIS_{t-1,t}\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)}
\end{aligned}$$

since $EIS_{t-1,t} > 0$ this implies

$$\frac{EIS_{t,t+1}}{EIS_{t-1,t}} < 1$$

$$EIS_{t,t+1} < EIS_{t-1,t}$$

Therefore the pro-cyclicality of the EIS parameter implies pro-cyclical EIS.

Case 3: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t \to \{s_t, s_{t+1}\} \in \Delta^u_{t+1}$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t$. So the EIS at time $t-1$ is again, just $EIS_{t-1,t} = \psi_t$. Now, suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta^u_{t+1}$ so that $G_t < G_{t+1}$, which by the pro-cyclicality of ψ_t implies $\psi_{t+1} > \psi_t$ and hence $\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right) < 0$. Notice that since EIS is always positive that

$$\frac{EIS_{t,t+1}}{EIS_{t-1,t}} > 0$$

and since $M_{t,t+1} \geq 0$ and $G_{t+1} \geq 0$ (the gross consumption growth rate) we have

$$0 < \frac{1 + M_{t,t+1}G_{t+1}}{(1 + M_{t,t+1}G_{t+1}) + EIS_{t-1,t}\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)}$$

but since $\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right) < 0$ and $EIS_{t-1,t} > 0$ we know

$$(1 + M_{t,t+1}G_{t+1}) + EIS_{t-1,t}\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right) < (1 + M_{t,t+1}G_{t+1})$$

which implies

$$\frac{EIS_{t,t+1}}{EIS_{t-1,t}} = \frac{1 + M_{t,t+1}G_{t+1}}{(1 + M_{t,t+1}G_{t+1}) + EIS_{t-1,t}\left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} > 1$$

hence

$$\frac{EIS_{t,t+1}}{EIS_{t-1,t}} > 1$$
$$EIS_{t,t+1} > EIS_{t-1,t}$$

Therefore the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 4: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \mathcal{S}_t \rightarrow \{s_t, s_{t+1}\} \in \Delta^m_{t+1}$

Under the assumption restricting the joint Markov process, the set $\Delta^m_{t+1} = \emptyset$. Therefore, these transition paths are irrelevant.

Case 5: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta^d_t \rightarrow \{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta^d_t$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$. So we know $EIS_{t,t+1} = \psi_t$ and $G_{t-1} > G_t$ which implies $\psi_{t-1} > \psi_t$ so that

$$\begin{aligned}
EIS_{t-1,t} &= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right) + \left(\frac{1}{\psi_t} - \frac{1}{\psi_{t-1}}\right)} \\
&= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(M_{t-1,t}G_t\right) + \frac{1}{\psi_t}} > \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_t}\left(M_{t-1,t}G_t\right) + \frac{1}{\psi_t}} \\
&= \psi_t = EIS_{t,t+1} \\
EIS_{t-1,t} &> EIS_{t,t+1}
\end{aligned}$$

Therefore the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 6: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u \rightarrow \{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$. So we know $EIS_{t,t+1} = \psi_t$ and $G_{t-1} < G_t$ which implies $\psi_{t-1} < \psi_t$ so that

$$\begin{aligned}
EIS_{t-1,t} &= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right) + \left(\frac{1}{\psi_t} - \frac{1}{\psi_{t-1}}\right)} \\
&= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(M_{t-1,t}G_t\right) + \frac{1}{\psi_t}} < \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_t}\left(M_{t-1,t}G_t\right) + \frac{1}{\psi_t}} \\
&= \psi_t = EIS_{t,t+1} \\
EIS_{t-1,t} &< EIS_{t,t+1}
\end{aligned}$$

Therefore the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 7: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^m \rightarrow \{s_t, s_{t+1}\} \in \mathcal{S}_{t+1}$

Under the assumption restricting the joint Markov process, the set $\Delta_t^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 8: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^u$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta_{t+1}^u$. So we know $G_{t-1} < G_t$ and $G_t < G_{t+1}$ which by the cyclicality of the EIS parameter implies $\psi_{t-1} < \psi_t$ and $\psi_t < \psi_{t+1}$. It follows that

$$EIS_{t,t+1} = \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t,t+1}G_{t+1}\right) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} > \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t-1,t}G_t\right)} = \psi_t$$

Now consider rewriting $EIS_{t-1,t}$ as follows

$$\begin{aligned} EIS_{t-1,t} &= \frac{1+M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1+M_{t-1,t}G_t\right)+\left(\frac{1}{\psi_t}-\frac{1}{\psi_{t-1}}\right)} = \frac{1+M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(M_{t-1,t}G_t\right)+\frac{1}{\psi_t}} \\ &= \frac{\psi_{t-1}\psi_t\left(1+M_{t-1,t}G_t\right)}{\psi_t\left(M_{t-1,t}G_t\right)+\psi_{t-1}} < \frac{\psi_{t-1}\psi_t\left(1+M_{t-1,t}G_t\right)}{\psi_{t-1}\left(M_{t-1,t}G_t\right)+\psi_{t-1}} \\ &= \frac{\psi_{t-1}\psi_t\left(1+M_{t-1,t}G_t\right)}{\psi_{t-1}\left(1+M_{t-1,t}G_t\right)} = \psi_t \end{aligned}$$

Where the inequality follows from the fact that $\psi_{t-1} < \psi_t$. Since $EIS_{t-1,t} < \psi_t$ it follows from above that $EIS_{t-1,t} < EIS_{t,t+1}$. Hence the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 9: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u \to \{s_t, s_{t+1}\} \in \Delta_{t+1}^m$

Under the assumption restricting the joint Markov process, the set $\Delta_{t+1}^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 10: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u \to \{s_t, s_{t+1}\} \in \Delta_{t+1}^d$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^u$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta_{t+1}^d$. So we know $G_{t-1} < g_t$ and $g_t > g_{t+1}$ which by the cyclicality of the EIS parameter implies $\psi_{t-1} < \psi_t$ and $\psi_t > \psi_{t+1}$. It follows that

$$\begin{aligned} EIS_{t-1,t} &= \frac{1+M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1+M_{t-1,t}G_t\right)+\left(\frac{1}{\psi_t}-\frac{1}{\psi_{t-1}}\right)} < \frac{1+M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1+M_{t-1,t}G_t\right)} = \psi_{t-1} \\ EIS_{t,t+1} &= \frac{1+M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1+M_{t,t+1}G_{t+1}\right)+\left(\frac{1}{\psi_{t+1}}-\frac{1}{\psi_t}\right)} < \frac{1+M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1+M_{t-1,t}G_t\right)} = \psi_t \end{aligned}$$

which implies

$$\frac{EIS_{t-1,t}}{EIS_{t,t+1}} < \frac{\psi_{t-1}}{\psi_t}$$

and since $\psi_{t-1} < \psi_t$ it follows that

$$\frac{EIS_{t-1,t}}{EIS_{t,t+1}} < \frac{\psi_{t-1}}{\psi_t} < 1$$

$$EIS_{t-1,t} < EIS_{t,t+1}$$

Therefore the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 11: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^m \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^m$

Under the assumption restricting the joint Markov process, the sets $\Delta_{t+1}^m = \emptyset$ and $\Delta_t^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 12: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^m \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^u$

Under the assumption restricting the joint Markov process, the set $\Delta_t^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 13: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^m \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^d$

Under the assumption restricting the joint Markov process, the set $\Delta_t^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 14: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^d \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^d$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^d$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta_{t+1}^d$. So we know $G_{t-1} > G_t$ and $G_t > G_{t+1}$ which by the cyclicality of the EIS parameter implies $\psi_{t-1} > \psi_t$ and $\psi_t > \psi_{t+1}$. It follows that

$$EIS_{t,t+1} = \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t,t+1}G_{t+1}\right) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} < \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t-1,t}G_t\right)} = \psi_t$$

Now consider rewriting $EIS_{t-1,t}$ as follows

$$\begin{aligned}
EIS_{t-1,t} &= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right) + \left(\frac{1}{\psi_t} - \frac{1}{\psi_{t-1}}\right)} = \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(M_{t-1,t}G_t\right) + \frac{1}{\psi_t}} \\
&= \frac{\psi_{t-1}\psi_t\left(1 + M_{t-1,t}G_t\right)}{\psi_t\left(M_{t-1,t}G_t\right) + \psi_{t-1}} > \frac{\psi_{t-1}\psi_t\left(1 + M_{t-1,t}G_t\right)}{\psi_{t-1}\left(M_{t-1,t}G_t\right) + \psi_{t-1}} \\
&= \frac{\psi_{t-1}\psi_t\left(1 + M_{t-1,t}G_t\right)}{\psi_{t-1}\left(1 + M_{t-1,t}G_t\right)} = \psi_t
\end{aligned}$$

Where the inequality follows from the fact that $\psi_{t-1} > \psi_t$. Since $EIS_{t-1,t} > \psi_t$ it follows from above that $EIS_{t,t+1} < EIS_{t-1,t}$. Hence the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS.

Case 15: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^d \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^m$

Under the assumption restricting the joint Markov process, the set $\Delta_{t+1}^m = \emptyset$. Therefore, these transition paths are irrelevant.

Case 16: $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^d \rightarrow \{s_t, s_{t+1}\} \in \Delta_{t+1}^u$

Consider any $\{\tilde{s}_{t-1}, \tilde{s}_t\} \in \Delta_t^d$ and suppose at time t that we transition to any $\{s_t, s_{t+1}\} \in \Delta_{t+1}^u$. So we know $G_{t-1} > G_t$ and $G_t < G_{t+1}$ which by the cyclicality of the EIS parameter implies $\psi_{t-1} > \psi_t$ and $\psi_t < \psi_{t+1}$. It follows that

$$
\begin{aligned}
EIS_{t-1,t} &= \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right) + \left(\frac{1}{\psi_t} - \frac{1}{\psi_{t-1}}\right)} > \frac{1 + M_{t-1,t}G_t}{\frac{1}{\psi_{t-1}}\left(1 + M_{t-1,t}G_t\right)} = \psi_{t-1} \\
EIS_{t,t+1} &= \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t,t+1}G_{t+1}\right) + \left(\frac{1}{\psi_{t+1}} - \frac{1}{\psi_t}\right)} > \frac{1 + M_{t,t+1}G_{t+1}}{\frac{1}{\psi_t}\left(1 + M_{t-1,t}G_t\right)} = \psi_t
\end{aligned}
$$

which implies

$$
\frac{EIS_{t-1,t}}{EIS_{t,t+1}} > \frac{\psi_{t-1}}{\psi_t}
$$

and since $\psi_{t-1} > \psi_t$ it follows that

$$
\begin{aligned}
\frac{EIS_{t-1,t}}{EIS_{t,t+1}} > \frac{\psi_{t-1}}{\psi_t} > 1 \\
EIS_{t-1,t} > EIS_{t,t+1}
\end{aligned}
$$

Hence the pro-cyclical nature of the EIS parameter implies pro-cyclical EIS. We have shown that this holds for every possible transition path for the state variable s_t, therefore pro-cyclicality of the EIS parameter ψ_t implies the $EIS_{t,t+1}$ is pro-cyclical. $\square$

A.6 Full Predictability Results

Table 37

Full Predictability Results - Alternative Calibrations

This table reports predictability of excess returns, consumption and dividend growth over one, three and five year horizons at an annual frequency for the calibrations in Table 1. The data sample is 1930-2013 and all coefficients and R-squared eestimates within each panel are jointly estimated using the GMM method of Hansen and Singleton (1982) and 5 Newey West lags for heteroskedasticity and autocorrelation consistent standard errors. The coefficient estimates are in units of basis points (e.g. $\beta = 0.0001$ is 0.01% or 1 basis point). Calibrations (1-3) are special cases of the baseline calibration, shutting down time variation in risk aversion ($b = 0$), the EIS parameter ($d = 0$) or both ($b = 0$ and $d = 0$) and are otherwise identical to the baseline calibration. Calibration (4) with $\rho_C = 0$ is an alternative calibration from the baseline that specifies consumption growth as an iid process. Calibrations (1b) and (2b) are alternative calibrations from the baseline that best fit two special cases of the model when time variation in risk aversion ($b = 0$) or the EIS parameter ($d = 0$) is shut down.

					Baseline Special Cases								Best Fit			
					(1)		(2)		(3)		(4)		(1b)		(2b)	
	Data				$b = 0$		$d = 0$		$b = 0$, $d = 0$		$\rho_C = 0$		$b = 0$		$d = 0$	
Time Varying Risk Aversion					N		Y		N		Y		N		Y	
Time Varying EIS					Y		N		N		Y		Y		N	
	$\hat{\beta}$	95% CI	$\hat{R}^2$	95% CI	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2	β	R^2
	$\Pi_{j=1}^{J}(1 + R_{m,t+j} - R_{f,t+j}) = \alpha + \beta PD_t + \epsilon_{t+j}$															
1Y	-0.002	[-0.004, -0.000]	0.033	[-0.033, 0.098]	-0.003	0.011	-0.020	0.058	0.001	0.000	-0.014	0.097	-0.004	0.011	-0.020	0.079
	(0.001)		(0.033)													
3Y	-0.007	[-0.012, -0.003]	0.128	[-0.029, 0.284]	-0.006	0.015	-0.047	0.109	0.002	0.000	-0.024	0.129	-0.008	0.016	-0.048	0.152
	(0.002)		(0.080)													
5Y	-0.015	[-0.022, -0.008]	0.225	[0.032, 0.418]	-0.007	0.013	-0.065	0.114	0.002	0.000	-0.028	0.111	-0.011	0.014	-0.066	0.165
	(0.004)		(0.099)													
	$\Pi_{j=1}^{J}\Delta C_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$															
1Y	0.0001	[-0.0002, 0.0005]	0.009	[-0.037, 0.056]	0.0000	0.000	0.0029	0.125	0.0050	0.221	0.0000	0.000	-0.0001	0.001	0.0023	0.118
	(0.0002)		(0.024)													
3Y	-0.0002	[-0.0009, 0.0006]	0.004	[-0.034, 0.043]	0.0000	0.000	0.0051	0.067	0.0088	0.119	0.0000	0.000	-0.0001	0.000	0.0041	0.064
	(0.0004)		(0.020)													
5Y	-0.0006	[-0.0016, 0.0003]	0.043	[-0.081, 0.167]	0.0000	0.000	0.0058	0.040	0.0100	0.071	0.0000	0.000	-0.0002	0.000	0.0047	0.038
	(0.0005)		(0.063)													
	$\Pi_{j=1}^{J}\Delta D_{t+j} = \alpha + \beta PD_t + \epsilon_{t+j}$															
1Y	0.0013	[-0.0009, 0.0036]	0.029	[-0.045, 0.102]	0.0000	0.000	0.0131	0.125	0.0226	0.221	0.0000	0.000	-0.0005	0.001	0.0100	0.118
	(0.0011)		(0.037)													
3Y	0.0015	[-0.0020, 0.0051]	0.012	[-0.038, 0.062]	0.0000	0.000	0.0231	0.067	0.0398	0.118	0.0000	0.000	-0.0008	0.000	0.0175	0.063
	(0.0018)		(0.025)													
5Y	0.0014	[-0.0022, 0.0051]	0.011	[-0.049, 0.072]	0.0000	0.000	0.0264	0.040	0.0456	0.070	0.0000	0.000	-0.0010	0.000	0.0201	0.037
	(0.0018)		(0.031)													
	$PD_{t+1} = \alpha + \beta\Pi_{j=1}^{J}\Delta C_{t+1-j} + \epsilon_{t+j}$															
1Y	-3.78	[-186.83, 179.28]	0.000	[-0.002, 0.002]	-38.68	0.027	52.48	0.186	44.03	0.221	-17.79	0.006	-45.27	0.033	62.09	0.179
	(93.40)		(0.001)													
3Y	-35.69	[-109.63, 38.25]	0.012	[-0.037, 0.060]	-21.83	0.049	18.54	0.133	13.47	0.119	-9.85	0.006	-23.81	0.052	22.10	0.130
	(37.72)		(0.025)													
5Y	-55.10	[-128.94, 18.75]	0.035	[-0.060, 0.129]	-14.72	0.048	10.66	0.095	7.10	0.071	-6.24	0.005	-15.88	0.050	12.77	0.093
	(37.68)		(0.048)													

A.7 Full Estimation Tables

Table 38

Marginal Revenue Product of Star College Football Players. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	1246194.1***	2110456.4**	1772393.3***	635939.4**	620915.0**	634448.8**
	(371109.5)	(933544.5)	(557169.9)	(273501.0)	(258687.2)	(283630.8)
Stars_{t-1}	784531.3*	1541987.4**	2125693.1***	463500.0**	482399.8**	629070.6***
	(407013.3)	(746867.3)	(613806.8)	(209543.1)	(199374.2)	(222252.8)
Stars_{t-2}	549369.2	-211988.4	135553.5	2163.8	131353.3	156726.8
	(409714.8)	(625430.4)	(497226.6)	(191799.8)	(217898.7)	(230384.4)
Wins_{t-1}	-33715.1	2350.5	-65521.4	17886.1	10689.7	2674.8
	(105185.3)	(95311.6)	(101668.3)	(102868.0)	(101990.9)	(101220.6)
Wins_{t-2}	47950.9	102288.3	84403.1	94650.6	77305.9	74126.7
	(56749.6)	(61649.3)	(62019.0)	(66211.5)	(68658.6)	(65450.8)
CoachCareer_{t-1}	2571657.5	1933681.0	2473963.0	1252014.5	1252673.2	1423088.7
	(2077061.6)	(2066798.6)	(2083839.1)	(2063261.0)	(2066246.2)	(2077016.9)
CoachChange	-219077.0	-141394.1	-167370.1	-90464.0	-71287.1	-78582.5
	(319562.9)	(307939.1)	(305613.8)	(316793.4)	(317650.5)	(315596.4)
BowlGame_{t-1}	862673.1*	696357.4	805688.7*	612201.2	626535.5	622163.7
	(463602.8)	(443760.2)	(457479.2)	(458303.6)	(455531.3)	(452238.2)
BowlWin_{t-1}	-367095.4	-228156.7	-186535.8	-379685.7	-393601.2	-391951.8
	(417701.8)	(426506.3)	(401965.8)	(424937.9)	(427281.8)	(427480.3)
SOS	4271.7	14754.5	10927.6	43752.0	44927.4	43343.3
	(53786.2)	(57691.0)	(55885.7)	(57116.1)	(56724.4)	(56769.4)
TDPts		-78863.2	-64150.4	-57364.1	-53461.7	-53654.6
		(76314.7)	(72631.8)	(77264.9)	(77646.9)	(77439.7)
TDYds		1500386.6	1657437.3	950269.4	1025833.8	1087674.7
		(2959422.3)	(2991585.0)	(3050531.6)	(3049305.4)	(3027356.8)
TDPassYds		-1497058.4	-1654554.4	-948102.7	-1023268.2	-1085497.0
		(2959896.7)	(2992292.3)	(3051440.0)	(3050172.4)	(3028225.1)
TDPassTDs		-751663.0	-742934.7	-919743.8	-969915.2	-952002.9
		(785910.7)	(771658.0)	(780685.2)	(780771.1)	(773783.8)
TDRushYds		-1495327.3	-1653492.3	-946798.2	-1022720.0	-1084533.8
		(2959229.5)	(2991477.6)	(3050698.3)	(3049472.3)	(3027495.9)
TDRushTDs		327305.5	260740.1	238916.9	246696.6	279805.0
		(636022.6)	(610659.0)	(652031.6)	(656716.1)	(650560.1)

HistWins	-21868.4	-15778.1	-13973.0	-28041.5	-29499.3	-27052.4
	(46763.7)	(51021.9)	(50663.7)	(50885.8)	(50808.9)	(50762.5)
HistBowls	-489220.2	-527785.0	-491664.8	-481393.7	-480626.9	-500249.5
	(347974.5)	(362683.0)	(359855.6)	(369600.2)	(368296.9)	(365399.9)
HistBowlWins	404944.6	396534.3	346237.0	477048.1	477640.9	455972.0
	(431381.2)	(438590.6)	(435241.9)	(454890.1)	(453306.9)	(445922.6)
Distance	-24893.5	-26074.5	-25418.8	-20941.5	-20871.2	-21590.8
	(16516.5)	(17347.0)	(17021.0)	(17282.3)	(17333.0)	(17225.4)
UndergradPop	-138243.3	-199825.2	-212833.2	-174896.7	-161813.5	-139273.3
	(206439.8)	(207066.6)	(204399.3)	(206220.2)	(204779.1)	(201240.2)
PerCapPI	184142.6	257071.2	271520.4	218391.4	212482.4	204275.8
	(319267.5)	(335018.5)	(322485.3)	(329132.8)	(328377.7)	(322979.3)
GrPerCapPI	20459.3	16687.3	7857.6	4989.6	11021.8	17480.4
	(128637.6)	(127462.8)	(126174.2)	(129573.2)	(128469.5)	(128432.2)
CityPop	12642171.7	-7324344.3	-7259534.8	4158844.5	5759898.7	2590694.1
	(25034085.1)	(29139427.5)	(27668730.0)	(30375296.5)	(30644687.1)	(30155684.9)
StatePop	10569.9	-122667.0	-170673.5	91495.6	102759.9	139855.1
	(4089596.0)	(4150891.0)	(4208402.6)	(4162556.3)	(4199445.6)	(4138946.2)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.773	0.775	0.779	0.774	0.774	0.774
Adjusted R^2	0.972	0.972	0.972	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 39

Marginal Revenue Product of Star College Football Players by Position. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.2) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDYds	(6) PER
Star QB	4608930.9***	3471509.8**	2214355.5**	1019893.4**	924894.5**	850420.6*
	(1164765.0)	(1351570.5)	(934112.1)	(478396.0)	(392270.5)	(481015.0)
Star RB	301788.4	608943.1	1048518.4	488427.7	421584.8	444569.6
	(631539.7)	(1309714.5)	(915890.6)	(429620.5)	(414200.9)	(418953.7)
Star WR	2905696.8**	-767266.6	2472387.2	464649.9	423843.9	576679.4

	(1405377.0)	(3344772.8)	(1949165.7)	(536098.5)	(544325.4)	(516914.8)
Star TE	1276488.1					
	(1060995.6)					
Star OL	1817052.2					
	(1902022.5)					
Star K	-1413320.6					
	(917291.1)					
Star P	2254073.1					
	(2391757.8)					
Star LB	1343434.9					
	(1161464.0)					
Star DB	900250.4					
	(809392.0)					
Star DL	-152692.0					
	(1029483.9)					
Star QB_{t-1}	2607322.5	1616299.2	2736083.1***	521386.4	612889.9	1334497.5**
	(2006577.4)	(1059789.0)	(826011.0)	(524194.5)	(486862.9)	(626311.7)
Star RB_{t-1}	421282.0	995844.6	804851.1	514506.9	527243.5	527565.3
	(1348817.2)	(1496832.9)	(1143632.9)	(452007.8)	(446920.2)	(447038.5)
Star WR_{t-1}	2163652.1	527242.2	3184923.0	376250.6	323235.6	300713.9
	(1341206.1)	(3141604.3)	(2157792.0)	(411840.5)	(422264.0)	(394164.2)
Star TE_{t-1}	1581637.5					
	(1089486.2)					
Star OL_{t-1}	-779066.9					
	(1958113.3)					
Star K_{t-1}	-2275590.3*					
	(1169638.9)					
Star P_{t-1}	845999.7					
	(1355701.1)					
Star LB_{t-1}	-222293.2					
	(841733.8)					
Star DB_{t-1}	1410565.2					
	(1061535.3)					
Star DL_{t-1}	-877913.4					
	(1144656.4)					
Star QB_{t-2}	222676.6	970598.2	1242415.4*	283381.3	844437.1	1215640.2*
	(1646554.8)	(844426.8)	(630114.6)	(531849.9)	(595708.5)	(622824.9)
Star RB_{t-2}	-291669.7	-1886976.8	-1752297.4*	-291948.0	-272552.0	-248493.1
	(1031439.8)	(1441911.8)	(927098.0)	(455772.0)	(448109.3)	(436319.5)
Star WR_{t-2}	984218.9	-1581986.8	165715.1	29221.4	-129764.1	-115558.6
	(860688.3)	(2279872.5)	(1416804.7)	(394391.0)	(404670.7)	(378890.5)
Star TE_{t-2}	2402861.2					
	(1891760.7)					
Star OL_{t-2}	-593484.6					
	(1731323.7)					
Star K_{t-2}	-1486708.5					
	(1444019.2)					
Star P_{t-2}	-1225415.9					
	(1463157.4)					
Star LB_{t-2}	938578.5					

	(1402728.0)					
Star DB$_{t-2}$	1134369.4					
	(940905.3)					
Star DL$_{t-2}$	412546.1					
	(1213959.7)					
Wins$_{t-1}$	-52336.9	11531.0	-81840.9	11875.8	7538.6	-23485.3
	(106419.9)	(97070.3)	(104071.1)	(106889.6)	(105521.7)	(106066.1)
Wins$_{t-2}$	38390.7	99251.1	79031.0	95108.3	65122.9	63821.0
	(57716.3)	(63047.3)	(64175.8)	(71878.1)	(77026.1)	(70326.5)
CoachCareer$_{t-1}$	3213553.8	1835760.3	2627403.3	1319614.2	1355460.9	1706857.8
	(2134175.4)	(2025476.9)	(2079157.4)	(2120277.5)	(2104740.1)	(2143148.5)
CoachChange	-231065.5	-121945.0	-163568.0	-85606.8	-81523.4	-108553.3
	(307360.7)	(303639.0)	(311992.4)	(314014.5)	(315913.8)	(312753.5)
BowlGame$_{t-1}$	777880.6*	658882.5	835970.0*	639978.7	660592.3	700971.8
	(438856.7)	(448743.3)	(467343.8)	(463505.2)	(457427.3)	(459879.4)
BowlWin$_{t-1}$	-308446.0	-240996.5	-151007.2	-379342.0	-406487.8	-382459.2
	(401160.9)	(432680.8)	(400402.2)	(426606.3)	(429053.6)	(427362.6)
SOS	19470.9	14867.5	20330.5	42959.8	39048.9	42425.0
	(52473.9)	(59897.4)	(57990.2)	(57924.7)	(57893.6)	(58254.1)
TDPts		-76570.0	-70043.3	-54291.3	-45022.7	-54743.2
		(76028.0)	(72883.5)	(78084.4)	(77528.8)	(77546.7)
TDYds		1351330.1	1601607.0	965753.3	1097500.7	1484895.8
		(2992151.0)	(2980740.9)	(3003318.5)	(3003149.9)	(3007275.4)
TDPassYds		-1347939.7	-1598624.7	-963620.0	-1094602.7	-1483540.0
		(2992470.3)	(2981402.8)	(3004145.8)	(3003977.1)	(3008135.5)
TDPassTDs		-794188.3	-729846.2	-945375.5	-1040211.1	-930344.2
		(789236.0)	(773235.5)	(773754.7)	(772104.6)	(762462.3)
TDRushYds		-1345858.4	-1597042.7	-962289.6	-1094454.2	-1482186.1
		(2992074.7)	(2980555.7)	(3003419.3)	(3003282.3)	(3007327.0)
TDRushTDs		302388.4	298673.9	216929.3	193897.5	330587.5
		(635163.7)	(619666.6)	(657399.7)	(655205.6)	(658114.3)
HistWins	-23758.9	-24106.9	-24122.7	-30798.3	-37716.8	-34010.9
	(49766.3)	(51678.6)	(51016.7)	(51136.4)	(51501.7)	(51445.5)
HistBowls	-515923.9	-474251.6	-452495.4	-456432.9	-452180.6	-480332.2
	(368178.1)	(361817.6)	(361365.3)	(363918.4)	(358918.6)	(358232.0)
HistBowlWins	466421.6	445286.4	440893.7	490069.0	510823.1	465463.3
	(448103.8)	(433391.5)	(446533.0)	(455338.5)	(449406.3)	(441247.3)
Distance	-21569.8	-23639.4	-22686.0	-21075.3	-20994.4	-23309.0
	(17363.9)	(17401.6)	(16776.1)	(17260.4)	(17163.4)	(17294.5)
UndergradPop	-161144.1	-193149.6	-240074.6	-180239.3	-169777.3	-120250.4
	(213332.5)	(207897.3)	(211872.7)	(208366.3)	(206100.6)	(200985.9)
PerCapPI	85935.8	247697.6	259538.2	209177.1	196049.1	192825.7
	(294998.2)	(337534.0)	(326460.5)	(331948.0)	(332823.7)	(328663.7)
GrPerCapPI	9221.3	14574.6	952.0	1340.5	9013.6	30709.9
	(126126.2)	(128483.3)	(125401.1)	(130548.6)	(130146.6)	(131524.1)
CityPop	-9218094.6	-1782102.5	-11199866.7	6515370.4	10912586.8	5272433.8
	(26430954.7)	(30818562.4)	(28836276.3)	(29774863.2)	(31018994.5)	(30524539.7)
StatePop	-869332.4	-115674.4	-53742.7	-21432.8	80254.8	386332.3
	(3675206.2)	(4211033.9)	(4277078.3)	(4184630.6)	(4261748.9)	(4226497.2)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.784	0.777	0.782	0.774	0.775	0.776
Adjusted R^2	0.972	0.972	0.973	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 40

Marginal Revenue Product of Star College Basketball Players. This table reports fixed effects estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1087765.3**	654710.8***	345336.8**	204304.3**	382382.2**	402533.9**	310260.3*	319721.4**
	(493080.3)	(194042.4)	(171755.6)	(88775.4)	(191897.4)	(192852.0)	(181824.4)	(145587.1)
Stars_{t-1}	217558.3	12327.7	88669.0	-11202.2	186547.7	-5263.1	14561.2	30787.2
	(374357.0)	(291240.1)	(177561.3)	(88077.2)	(294223.2)	(228566.6)	(102755.7)	(81964.0)
Stars_{t-2}	205491.5	149084.8	207909.7	224483.7**	252300.1	106031.9	174220.5	80851.8
	(336928.1)	(215135.9)	(157622.5)	(100847.0)	(245098.3)	(202592.1)	(113390.1)	(85780.5)
Wins_{t-1}	5500.7	4737.6	4803.9	6675.7	4912.5	5211.9	5529.2	4768.9
	(4740.8)	(4654.8)	(4704.4)	(4620.0)	(4565.3)	(4611.5)	(4768.7)	(4879.6)
Wins_{t-2}	11700.8***	11033.7**	10379.1**	7470.9	11046.7***	11099.0***	10877.3**	10851.1**
	(4346.4)	(4372.0)	(4388.4)	(4631.2)	(3932.6)	(4106.4)	(4501.2)	(4605.0)
$\text{CoachCarTourn}_{t-1}$	53036.4***	53587.8***	52917.5***	53109.5***	53300.7***	54220.0***	54132.1***	52295.5***
	(16309.4)	(16423.3)	(16448.0)	(16397.5)	(16396.1)	(16327.9)	(16345.8)	(16446.8)
CoachCareer_{t-1}	-90371.2	-43852.9	-58691.2	-95287.7	-94945.2	-91601.0	-78380.4	-72456.0
	(296260.8)	(292797.7)	(296030.0)	(291734.8)	(294358.8)	(294552.7)	(295056.3)	(293596.7)
CoachChange	2584.2	-283.6	5442.5	5694.5	2596.8	2906.3	-2338.9	-1447.5
	(61633.1)	(61697.9)	(61112.9)	(61636.3)	(61858.0)	(61534.7)	(61566.3)	(61742.1)
NCAATourn_{t-1}	166471.4**	169729.4**	164773.6**	170940.6**	166791.3**	159770.3**	159670.5**	159186.5**
	(75438.0)	(74536.1)	(74413.7)	(76855.4)	(73208.1)	(75031.2)	(74594.7)	(75231.3)
Round2_{t-1}	-69474.9	-60521.7	-58626.8	-62519.4	-60851.5	-60525.5	-57685.2	-55454.7
	(127587.9)	(124549.9)	(129013.3)	(129844.1)	(129323.9)	(127547.7)	(128474.2)	(127233.5)
Sweet16_{t-1}	269822.6	259114.3	259282.3	311046.4*	280034.6	271213.4	303302.1*	287229.0*
	(175423.2)	(183746.1)	(180748.2)	(171514.0)	(180879.1)	(180337.0)	(175339.2)	(173614.7)
Elitet8_{t-1}	-139996.8	-144637.5	-92711.7	-21008.0	-120372.0	-100366.0	-118801.8	-125168.0
	(455596.0)	(460315.9)	(475971.8)	(438282.8)	(467622.7)	(476086.8)	(453607.7)	(452016.7)

Final4$_{t-1}$	343911.0	347028.2	372391.9	380139.1	356001.9	414610.1	391677.7	391363.2
	(375468.1)	(380341.5)	(371678.6)	(386948.9)	(412695.7)	(412792.3)	(392998.6)	(391782.5)
Final$_{t-1}$	-38560.7	32290.4	-66063.7	26618.6	-128696.6	-52997.7	-26463.4	-17221.9
	(260301.5)	(340616.9)	(299234.9)	(284129.2)	(314746.0)	(338112.3)	(267654.3)	(272431.6)
Champ$_{t-1}$	1766340.3**	1900785.4***	1899835.5***	2040793.9***	1793747.7**	1773651.1**	1822732.5***	1868723.7***
	(862499.7)	(574563.6)	(657183.3)	(647180.9)	(752011.7)	(736771.7)	(617623.3)	(618632.4)
NSchlsConf	1597.9	643.3	1146.6	2727.7	3598.7	2535.8	5855.1	4328.0
	(40495.4)	(40249.6)	(40056.5)	(40557.4)	(40108.9)	(40223.5)	(40202.9)	(40285.7)
NSchlsConfAP	-42507.0	-44208.6	-46226.4	-38351.2	-37726.9	-41862.1	-42184.5	-39373.7
	(40012.1)	(41527.4)	(41211.3)	(40894.9)	(41784.2)	(42282.7)	(40775.5)	(40345.1)
NSchlsConfTourn	5588.9	5151.3	4908.0	82.42	6918.3	6162.2	6446.4	7143.4
	(39038.3)	(38721.0)	(38681.8)	(38758.1)	(38824.8)	(38620.2)	(39511.7)	(39339.0)
NSchlsConfFF	-98339.8	-93396.3	-84183.4	-86897.0	-92170.3	-93787.2	-87031.1	-87327.8
	(82336.8)	(80792.0)	(81503.3)	(84174.2)	(80721.6)	(81051.3)	(81299.2)	(81085.9)
SOS	3171.8	2104.8	2277.8	1250.6	1571.2	1381.6	1359.0	388.3
	(12225.5)	(12177.8)	(12320.2)	(12193.9)	(12160.8)	(12107.1)	(12256.3)	(12319.4)
HistWins	-3339.3	-3489.0	-3692.1	-3790.9	-3766.7	-3604.8	-3403.5	-3287.8
	(2979.9)	(2973.0)	(2975.3)	(2986.8)	(3011.8)	(3032.5)	(2976.1)	(2966.4)
HistNCAATrn	-24692.0	-21625.1	-20544.8	-38894.2	-29861.0	-26729.9	-27267.5	-34361.8
	(59605.9)	(60731.5)	(60426.8)	(59135.1)	(60123.9)	(59840.0)	(60473.9)	(59837.3)
HistRound2	-70516.4	-48324.9	-46896.5	-60332.6	-65835.0	-71370.7	-62074.7	-66508.5
	(111100.2)	(112854.9)	(112528.5)	(112171.3)	(112792.9)	(112505.2)	(112727.3)	(112997.5)
HistSweet16	-105085.4	-108151.2	-90631.1	-56679.8	-77141.0	-70457.7	-96033.2	-100927.8
	(146123.0)	(146471.2)	(141988.0)	(137944.0)	(142556.4)	(142982.6)	(150636.9)	(149967.4)
HistElite8	122918.1	137631.2	151930.7	161923.4	127612.1	122314.2	98892.1	102881.1
	(189428.4)	(194172.7)	(195132.2)	(189286.0)	(189005.4)	(191677.5)	(195406.0)	(197563.2)
HistFinal4	288728.2	373800.4	405548.9	407783.7	314072.8	298481.2	319478.5	290306.4
	(312376.9)	(314445.6)	(316790.0)	(324777.9)	(316427.1)	(320106.9)	(323484.2)	(320863.9)
HistFinal	66589.0	215159.0	219301.6	148310.0	230876.8	215724.5	165225.1	178414.5
	(604624.8)	(590013.9)	(591344.3)	(577803.6)	(565544.9)	(570762.7)	(589264.2)	(593520.2)
HistChamp	-761595.7	-830886.5	-794815.5	-751941.5	-790368.2	-803171.5	-793072.3	-834846.1
	(864712.3)	(807223.6)	(802713.0)	(785328.2)	(792108.8)	(815147.9)	(796655.2)	(805341.5)
Distance	-1186.9	-1003.1	-1076.7	-1295.0	-1243.4	-1145.3	-1390.8	-1233.8
	(1555.8)	(1564.4)	(1548.8)	(1571.5)	(1593.4)	(1568.2)	(1542.9)	(1532.9)
UndergradPop	-51238.0	-48681.8	-50053.8	-46757.0	-48358.0	-47220.9	-44490.3	-45640.1

	(39268.9)	(38035.4)	(38894.5)	(39404.7)	(38536.3)	(39037.6)	(38722.6)	(38021.5)
PerCapPI	12632.5	10041.7	9382.0	2916.0	14931.7	14857.1	9983.7	9889.4
	(41123.9)	(40759.8)	(39747.8)	(40061.4)	(40497.9)	(40544.8)	(40065.8)	(40667.4)
GrPerCapPI	7602.4	9374.4	10665.1	11437.5	8135.4	10325.6	8650.5	10131.3
	(15679.9)	(15709.6)	(15623.5)	(15874.9)	(15719.9)	(15875.1)	(15642.0)	(15693.4)
CityPop	861614.4	918168.3	918507.3	882563.6	1056439.6	1089678.8	813444.8	790469.6
	(1896441.6)	(1857321.6)	(1871040.8)	(1896670.6)	(1849183.3)	(1837110.6)	(1861156.0)	(1887477.5)
StatePop	6654.2	59037.8	34208.8	77296.1	106871.3	103832.1	71506.4	90510.5
	(431937.2)	(407988.3)	(416686.1)	(429759.3)	(421011.7)	(421270.8)	(417325.0)	(424944.7)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.670	0.669	0.668	0.672	0.668	0.669	0.668	0.669
Adjusted R^2	0.968	0.968	0.968	0.969	0.968	0.968	0.968	0.968

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 41

Marginal Revenue Product of Star College Football Players - Discrete Measure. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different discrete measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	1062929.4***	2051659.7**	1766358.2***	634777.4**	605809.7**	616670.4**
	(323298.3)	(936657.7)	(551921.2)	(267899.3)	(251991.4)	(276390.5)
Stars_{t-1}	551891.3	1518086.1**	2103329.1***	458333.2**	461327.5**	600524.1***
	(344300.2)	(734827.8)	(605137.5)	(206375.5)	(194273.4)	(216799.7)
Stars_{t-2}	417832.9	-188455.0	146703.1	11668.6	132517.0	157749.8
	(356129.9)	(627577.9)	(492218.2)	(190181.8)	(215776.6)	(229355.4)
Wins_{t-1}	-27231.2	4158.1	-63777.2	17081.4	12992.2	5601.4
	(102417.3)	(95379.8)	(101454.9)	(102893.8)	(101681.6)	(100957.0)
Wins_{t-2}	50873.3	101411.6	83395.9	92623.3	76577.5	73520.9
	(55157.2)	(61689.7)	(62012.1)	(66321.5)	(68893.6)	(65860.7)
CoachCareer_{t-1}	2599678.9	1924428.4	2466749.7	1261797.4	1240299.6	1401226.6
	(2050449.2)	(2066560.1)	(2082921.4)	(2063484.7)	(2066252.3)	(2076842.8)
CoachChange	-245813.1	-141586.6	-165120.8	-88634.3	-70796.1	-79297.9
	(315570.1)	(308000.0)	(305454.2)	(317248.1)	(317641.2)	(315323.7)
BowlGame_{t-1}	820920.0*	692397.0	799736.1*	612761.4	623940.8	618465.1
	(455566.7)	(444160.5)	(457270.3)	(458518.9)	(455447.5)	(452236.2)
BowlWin_{t-1}	-376924.5	-230265.1	-189103.1	-377017.8	-394140.6	-394020.0
	(417213.6)	(426427.8)	(402269.7)	(424689.0)	(427523.6)	(427710.5)
SOS	-1020.0	15138.6	10712.1	43312.5	44019.0	42589.3
	(53829.9)	(57707.7)	(55873.3)	(57100.1)	(56750.4)	(56801.0)
TDPts		-79692.7	-64547.0	-57311.2	-54110.8	-54274.2
		(76474.7)	(72613.3)	(77176.8)	(77629.0)	(77468.0)
TDYds		1477484.4	1660810.1	942337.3	1019783.3	1064622.9
		(2959529.3)	(2991096.3)	(3051166.1)	(3049731.0)	(3028266.1)
TDPassYds		-1474201.8	-1657996.1	-940199.3	-1017197.3	-1062440.4
		(2960015.2)	(2991817.4)	(3052074.1)	(3050604.2)	(3029137.3)
TDPassTDs		-743696.4	-738882.2	-917040.1	-963800.8	-945139.4
		(787166.5)	(771871.2)	(779775.7)	(779646.5)	(773119.8)
TDRushYds		-1472448.7	-1656916.2	-938883.9	-1016670.8	-1061482.2
		(2959334.5)	(2990992.1)	(3051322.6)	(3049885.4)	(3028393.5)
TDRushTDs		334096.9	266543.4	240959.6	250649.9	282785.4
		(637357.3)	(610804.1)	(651548.9)	(656370.7)	(650819.4)
HistWins	-21083.1	-15825.1	-13798.1	-28203.2	-29254.9	-26796.9

	(47988.5)	(50993.9)	(50685.3)	(50918.2)	(50876.8)	(50815.9)
HistBowls	-489901.2	-527450.6	-491419.9	-480458.5	-478263.0	-497763.5
	(349342.7)	(362670.6)	(360016.5)	(369729.0)	(368490.3)	(365953.0)
HistBowlWins	353130.0	393628.9	344570.4	478785.4	473072.5	451164.3
	(432565.7)	(438187.4)	(434839.1)	(455271.2)	(452625.0)	(445541.7)
Distance	-25335.8	-26158.5	-25508.0	-20780.2	-21008.9	-21732.2
	(16575.0)	(17366.9)	(17033.4)	(17285.8)	(17352.2)	(17245.3)
UndergradPop	-144432.9	-198322.5	-211986.9	-175075.8	-161411.3	-138610.3
	(209157.6)	(207117.2)	(204483.3)	(206386.0)	(204727.8)	(201382.8)
PerCapPI	207362.8	258319.9	271139.1	218118.8	212022.8	204415.4
	(316857.0)	(335339.6)	(322526.2)	(328745.0)	(328520.8)	(323380.0)
GrPerCapPI	14993.7	16218.1	7780.2	5990.2	12818.8	19304.6
	(127251.5)	(127386.3)	(126064.8)	(129406.3)	(128288.8)	(128293.9)
CityPop	10299203.0	-7124452.5	-6802474.5	4040661.5	5240369.1	2240536.0
	(27464918.6)	(29198594.3)	(27623484.5)	(30326624.6)	(30749121.4)	(30342188.7)
StatePop	132676.4	-120170.4	-170546.6	128098.0	120093.6	159464.1
	(4062267.6)	(4156206.6)	(4210051.3)	(4153424.0)	(4193018.9)	(4134860.8)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.772	0.775	0.779	0.774	0.774	0.774
Adjusted R^2	0.972	0.972	0.972	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 42

Marginal Revenue Product of Star College Basketball Players - Discrete Measure. This table reports fixed effects regression estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1035975.5**	634754.2***	327818.2*	192254.3**	421983.3**	411124.2**	309455.9*	318445.0**
	(481752.9)	(192764.6)	(168625.4)	(83649.3)	(179149.7)	(180324.0)	(182795.1)	(145860.5)
Stars_{t-1}	194461.6	8473.9	82188.9	-14549.2	174676.9	-10149.0	13162.1	28743.7
	(371341.1)	(286415.5)	(172535.2)	(84974.2)	(283398.5)	(220033.8)	(103503.4)	(81866.8)
Stars_{t-2}	206669.7	153881.9	209186.9	220039.8**	213156.7	89265.3	175345.3	80635.9
	(331762.9)	(211748.9)	(154025.7)	(99184.1)	(241205.9)	(198312.6)	(114327.3)	(85592.8)
Wins_{t-1}	5529.0	4776.0	4846.5	6757.3	5020.8	5292.8	5551.4	4781.9
	(4742.3)	(4657.2)	(4705.6)	(4625.8)	(4575.1)	(4615.9)	(4769.6)	(4884.2)
Wins_{t-2}	11716.4***	11029.5**	10361.0**	7532.0	11243.5***	11273.8***	10862.3**	10847.6**
	(4345.4)	(4363.2)	(4380.1)	(4648.0)	(3962.6)	(4142.3)	(4503.1)	(4608.4)
$\text{CoachCarTourn}_{t-1}$	53083.7***	53626.0***	52935.3***	53162.8***	53551.0***	54305.4***	54136.9***	52288.7***
	(16306.9)	(16414.4)	(16429.4)	(16371.7)	(16406.8)	(16332.7)	(16346.1)	(16445.8)
CoachCareer_{t-1}	-91166.2	-44805.8	-60914.1	-98085.3	-102776.2	-96296.4	-78484.9	-72669.6
	(296381.7)	(292904.9)	(296076.0)	(291984.2)	(294665.7)	(294914.5)	(295065.4)	(293573.0)
CoachChange	2452.8	-275.9	5554.8	5264.0	2777.8	3317.3	-2090.3	-1125.0
	(61637.2)	(61708.8)	(61113.2)	(61690.5)	(61809.2)	(61528.5)	(61564.1)	(61732.9)
NCAATourn_{t-1}	165707.5**	169176.5**	164988.3**	170940.9**	164945.1**	158050.6**	159541.2**	159117.0**
	(75465.7)	(74520.5)	(74402.0)	(76866.8)	(73251.8)	(75267.2)	(74623.5)	(75248.3)
Round2_{t-1}	-69038.3	-60268.4	-58272.1	-62077.8	-61318.3	-62271.0	-57981.5	-55552.3
	(127659.3)	(124653.9)	(129193.8)	(130187.3)	(129248.8)	(127873.6)	(128511.4)	(127258.0)
Sweet16_{t-1}	270800.3	259998.1	261608.6	312686.6*	275681.2	268020.4	303088.9*	287116.1*
	(175680.1)	(183635.0)	(180615.3)	(172649.6)	(180518.7)	(180901.5)	(175329.3)	(173623.7)
Elitet8_{t-1}	-136884.7	-142804.7	-89478.4	-17143.5	-121840.4	-102216.9	-119136.7	-124414.5
	(455690.1)	(460409.7)	(475193.2)	(438530.6)	(466560.9)	(474973.5)	(453659.7)	(452048.6)

Final4_{t-1}	351632.7	349480.6	375530.9	386899.2	346330.2	413008.0	391612.5	390373.4
	(375564.4)	(379766.1)	(371722.8)	(384616.4)	(402529.2)	(407865.3)	(392964.8)	(391150.8)
Final_{t-1}	-33963.4	39289.0	-55952.2	37131.6	-123554.7	-48175.6	-26776.1	-16368.9
	(260029.9)	(339254.4)	(300001.4)	(278665.9)	(315417.5)	(338183.6)	(267683.9)	(272701.7)
Champ_{t-1}	1771496.1**	1903215.4***	1905184.0***	2042126.6***	1764883.6**	1724465.6**	1822491.5***	1870786.0***
	(865166.8)	(578110.3)	(658356.3)	(631771.2)	(718556.6)	(693729.8)	(617872.8)	(619292.9)
NSchlsConf	1680.8	639.0	1194.2	2868.0	3573.5	2461.5	5811.9	4360.0
	(40505.5)	(40251.9)	(40054.1)	(40551.9)	(40084.7)	(40195.2)	(40192.6)	(40279.9)
NSchlsConfAP	-42734.3	-44607.2	-46004.7	-38223.3	-38457.1	-42033.7	-42350.7	-39586.9
	(40109.3)	(41520.7)	(41206.0)	(40966.0)	(41838.3)	(42272.5)	(40773.7)	(40344.1)
NSchlsConfTourn	5858.7	5287.9	4848.0	108.4	7872.5	6481.5	6310.0	7005.5
	(39021.4)	(38716.5)	(38703.8)	(38766.4)	(38727.4)	(38561.1)	(39525.1)	(39340.4)
NSchlsConfFF	-98040.1	-93344.4	-84333.1	-87580.2	-93536.6	-94346.8	-87021.4	-87438.7
	(82226.0)	(80789.9)	(81426.7)	(84212.0)	(80549.9)	(80884.2)	(81286.1)	(81080.8)
SOS	3152.0	2133.5	2240.6	1193.0	1270.5	1198.2	1344.2	422.6
	(12216.2)	(12176.0)	(12321.9)	(12233.1)	(12124.3)	(12112.0)	(12256.3)	(12316.6)
HistWins	-3347.5	-3497.9	-3697.7	-3774.6	-3765.0	-3546.1	-3401.1	-3286.6
	(2980.6)	(2973.2)	(2974.4)	(2987.0)	(3014.2)	(3033.0)	(2975.9)	(2966.2)
HistNCAATrn	-24491.9	-21700.5	-20750.6	-38853.0	-29547.2	-26788.5	-27276.6	-34331.5
	(59651.6)	(60763.3)	(60443.4)	(59183.4)	(60076.5)	(59758.3)	(60474.4)	(59840.7)
HistRound2	-70874.2	-48177.2	-46950.6	-60957.0	-66607.8	-72361.7	-62110.5	-66557.2
	(111145.0)	(112891.4)	(112680.7)	(112134.6)	(112869.7)	(112441.7)	(112727.4)	(112991.8)
HistSweet16	-103854.7	-108188.9	-89588.0	-57247.4	-77118.8	-71718.5	-96102.1	-100915.3
	(146105.9)	(146550.0)	(142043.5)	(137908.8)	(142331.8)	(143020.5)	(150629.0)	(149977.7)
HistElite8	122300.6	138398.8	153850.8	162086.9	124354.5	121118.3	98796.8	103269.6
	(189441.3)	(193896.8)	(194892.6)	(188380.6)	(189793.4)	(191902.8)	(195405.5)	(197614.7)
HistFinal4	289465.5	377790.8	406189.7	415666.3	305769.2	293215.8	319416.5	291240.3
	(311958.6)	(315873.5)	(316946.9)	(325441.4)	(315849.6)	(318912.6)	(323489.2)	(320987.7)
HistFinal	76384.6	218851.3	222528.8	147453.3	233731.0	220428.5	165220.1	177643.2
	(604034.9)	(589117.3)	(590556.8)	(578323.8)	(564666.0)	(569304.5)	(589247.0)	(593586.4)
HistChamp	-757015.4	-831763.7	-795219.9	-747316.1	-787152.8	-807170.5	-793168.3	-835264.3
	(866337.1)	(807261.1)	(802923.5)	(786097.6)	(798581.3)	(818616.4)	(796598.1)	(805453.0)
Distance	-1192.0	-1013.8	-1077.2	-1318.0	-1227.4	-1162.8	-1394.8	-1237.0
	(1555.5)	(1563.9)	(1550.0)	(1570.9)	(1585.9)	(1563.3)	(1543.0)	(1533.2)
UndergradPop	-51259.9	-48763.9	-50143.6	-46632.0	-48126.5	-47259.7	-44468.6	-45673.7

	(39268.3)	(38059.1)	(38903.2)	(39431.3)	(38392.1)	(38942.3)	(38719.0)	(38026.7)
PerCapPI	12579.7	10218.0	9573.1	2809.1	15049.7	14994.5	10002.1	9902.9
	(41141.5)	(40770.1)	(39744.4)	(40066.6)	(40472.4)	(40552.3)	(40072.0)	(40656.6)
GrPerCapPI	7613.0	9297.5	10574.9	11407.1	8066.5	10435.9	8614.0	10130.2
	(15682.7)	(15716.1)	(15620.1)	(15868.6)	(15725.1)	(15893.2)	(15639.5)	(15687.9)
CityPop	863023.6	917742.1	917852.3	871686.9	1066028.3	1094021.0	814208.2	792952.1
	(1895758.1)	(1857622.1)	(1872259.8)	(1899514.2)	(1848478.2)	(1837561.0)	(1861378.2)	(1888037.6)
StatePop	8894.7	57700.6	32295.7	88462.9	109731.0	108940.9	71209.5	89252.1
	(431382.2)	(408344.6)	(417235.3)	(430550.1)	(420068.0)	(420439.0)	(417406.2)	(424929.5)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.669	0.669	0.668	0.672	0.668	0.669	0.668	0.669
Adjusted R^2	0.968	0.968	0.968	0.969	0.968	0.968	0.968	0.968

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 43

Marginal Revenue Product of Star College Football Players - Wins Included. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	926451.1**	1522818.2*	1177237.5**	273485.5	256650.6	277127.5
	(402026.1)	(889228.6)	(544071.6)	(305633.1)	(292662.4)	(304313.0)
Stars_{t-1}	714289.9*	1384924.8*	2087051.6***	407647.8*	420308.5**	550044.6**
	(401453.2)	(717023.7)	(612357.0)	(212809.1)	(202678.8)	(222842.6)
Stars_{t-2}	553711.2	-166349.4	64077.5	-26593.6	90578.7	135176.5
	(402675.8)	(622212.6)	(497332.3)	(189135.5)	(214063.2)	(225604.2)
Wins	274939.7***	348969.4***	351564.9***	353074.9***	354350.2***	359789.8***
	(74995.2)	(79970.3)	(78791.9)	(97875.9)	(98355.4)	(91981.8)
Wins_{t-1}	-7345.1	23825.2	-49181.1	42722.7	35500.1	26959.1
	(106403.2)	(96990.4)	(101631.9)	(104352.5)	(103815.1)	(102155.3)
Wins_{t-2}	111438.2*	149553.4**	133762.7**	143999.7**	128650.6*	124482.8*
	(61823.0)	(65103.8)	(65590.4)	(69353.3)	(71157.5)	(67503.3)
CoachCareer_{t-1}	2244305.0	1661061.4	2206707.1	1168961.9	1186148.5	1286603.7
	(1998891.1)	(1991400.9)	(2009452.1)	(1976103.4)	(1976750.1)	(1986751.7)
CoachChange	-55083.8	-29198.8	-62648.6	-12324.3	-3541.0	-514.7
	(305421.8)	(297499.9)	(294240.4)	(306141.2)	(307776.3)	(306411.0)
BowlGame_{t-1}	801635.7*	723398.0	845546.6*	622907.4	641113.7	646112.5
	(461419.2)	(439903.5)	(452157.6)	(451821.9)	(451479.1)	(448383.8)
BowlWin_{t-1}	-271550.9	-176341.5	-129392.2	-301405.2	-305649.5	-296419.7
	(407506.8)	(407253.4)	(387193.3)	(409197.9)	(412077.7)	(410269.2)
SOS	45560.8	29477.5	26287.0	50658.7	52705.6	52385.9
	(55548.3)	(58009.3)	(56205.9)	(57307.7)	(57051.7)	(57041.7)
TDPts		74672.2	84785.5	83866.3	82976.3	84887.9
		(83567.8)	(81452.0)	(86434.4)	(85962.2)	(84937.7)
TDYds		1158166.3	1305509.4	730781.6	747587.8	901059.4
		(2889808.5)	(2907281.6)	(2956665.7)	(2962185.4)	(2943115.8)
TDPassYds		-1161127.5	-1308425.5	-733965.1	-750574.5	-904544.3
		(2890623.5)	(2908321.2)	(2957886.9)	(2963352.7)	(2944318.7)
TDPassTDs		-1075468.6	-1071795.9	-1155084.1	-1160122.2	-1157127.4
		(763016.7)	(750287.5)	(762421.5)	(760016.8)	(754203.0)
TDRushYds		-1152505.8	-1300663.4	-725911.2	-742927.7	-896492.5
		(2889549.7)	(2907052.7)	(2956597.9)	(2962143.3)	(2943083.3)
TDRushTDs		-90349.1	-133409.4	-133326.8	-104657.9	-71493.2

		(641483.0)	(619525.5)	(654339.3)	(657695.1)	(652923.5)
HistWins	13532.2	9949.9	10333.7	-360.7	-1775.8	329.2
	(49402.3)	(52154.6)	(51783.3)	(53120.3)	(53010.1)	(52579.7)
HistBowls	-501296.9	-512727.8	-478500.4	-468326.5	-465992.1	-476874.5
	(346434.2)	(356643.2)	(354552.6)	(363926.7)	(363195.1)	(360418.9)
HistBowlWins	436554.0	376816.3	339666.7	415866.6	418814.4	410279.0
	(433675.7)	(438859.6)	(433828.8)	(453364.7)	(453213.5)	(445523.7)
Distance	-24424.5	-26603.5	-26341.1	-22643.4	-22404.8	-22828.6
	(16134.2)	(16540.2)	(16341.6)	(16320.0)	(16408.3)	(16331.7)
UndergradPop	-76567.4	-129901.7	-145432.6	-115893.4	-103678.5	-83662.8
	(204645.5)	(205740.9)	(202726.9)	(206019.8)	(205628.7)	(202931.6)
PerCapPI	225222.2	265734.4	275442.6	228780.8	226346.0	222839.1
	(308465.8)	(325624.8)	(315066.1)	(321018.5)	(320216.1)	(315866.4)
GrPerCapPI	-6672.3	-2557.0	-8119.6	-8332.0	-4664.3	-2066.0
	(127053.0)	(125048.5)	(124119.7)	(127343.9)	(126199.2)	(125789.1)
CityPop	10267321.2	-10874167.3	-10852029.7	-1933163.1	-704208.1	-2967084.0
	(25803325.3)	(31029740.9)	(28743940.4)	(32277043.2)	(32708796.7)	(32309187.1)
StatePop	-548663.0	-266620.9	-270917.6	-11510.8	659.7	28459.8
	(3848678.8)	(3889121.5)	(3939800.6)	(3874431.7)	(3903313.8)	(3860861.2)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.779	0.781	0.785	0.780	0.780	0.780

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 44

Marginal Revenue Product of Star College Football Players by Position - Wins Included. This table reports fixed effects regression estimates of a star football player's marginal revenue product from Model (2.2) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDYds	(6) PER
Star QB	4002896.6***	2613205.7*	1338255.8	426270.7	344168.7	381371.0
	(1144409.0)	(1322656.6)	(921253.7)	(504839.4)	(424145.3)	(479613.7)
Star RB	-71395.5	287602.6	822523.3	164893.3	117441.0	127832.2
	(626403.8)	(1260993.0)	(914857.0)	(446548.7)	(437817.1)	(441013.1)
Star WR	2671726.0*	-430341.1	2275417.0	250983.5	230554.0	272862.4

	(1379730.4)	(3370752.1)	(1911482.0)	(534304.1)	(543821.9)	(521004.1)
Star TE	709435.3					
	(1101329.7)					
Star OL	1441320.6					
	(1894931.1)					
Star K	-1713721.1*					
	(943726.6)					
Star P	2240380.6					
	(2448445.7)					
Star LB	1100736.3					
	(1199072.9)					
Star DB	514531.4					
	(879917.8)					
Star DL	-343706.0					
	(1057113.1)					
Wins	273964.8***	330986.2***	357280.0***	347714.3***	345097.5***	352589.0***
	(73651.1)	(76827.9)	(76999.7)	(99527.1)	(99837.8)	(91104.1)
Star QB_{t-1}	2611597.4	1490620.9	2684710.6***	425406.8	515950.5	1172038.1*
	(1955824.1)	(1053164.0)	(814824.0)	(516100.8)	(483480.0)	(602783.9)
Star RB_{t-1}	323916.9	895299.9	810298.9	455126.4	463177.9	456263.1
	(1239196.0)	(1503292.4)	(1132294.3)	(448895.1)	(446222.7)	(446421.7)
Star WR_{t-1}	2038881.9	509920.8	3318746.5	361750.8	300917.1	264215.1
	(1315882.4)	(2867703.5)	(2131557.1)	(405450.3)	(419007.1)	(386977.8)
Star TE_{t-1}	1447442.1					
	(1094682.6)					
Star OL_{t-1}	-777566.8					
	(1822117.5)					
Star K_{t-1}	-2374622.5*					
	(1315189.9)					
Star P_{t-1}	538349.8					
	(1336473.7)					
Star LB_{t-1}	-282106.8					
	(846489.4)					
Star DB_{t-1}	1334047.2					
	(1070753.7)					
Star DL_{t-1}	-970607.7					
	(1124523.7)					
Star QB_{t-2}	518013.2	877899.6	1180250.7*	139692.4	665871.4	1118972.1*
	(1592941.8)	(845853.0)	(651010.3)	(524457.7)	(601209.9)	(618899.0)
Star RB_{t-2}	-366207.2	-1709926.3	-1882554.0**	-271338.9	-257297.4	-253156.5
	(989744.5)	(1443421.8)	(924455.5)	(447091.1)	(440654.0)	(431273.5)
Star WR_{t-2}	879686.7	-1207240.5	152284.6	33209.9	-116997.9	-114984.8
	(854836.2)	(2292921.4)	(1344609.2)	(370415.3)	(386422.3)	(358751.9)
Star TE_{t-2}	2437961.3					
	(1905816.6)					
Star OL_{t-2}	-416375.1					
	(1585694.0)					
Star K_{t-2}	-1459077.4					
	(1402101.4)					
Star P_{t-2}	-1134644.3					

	(1464326.1)					
Star LB_{t-2}	978819.0					
	(1382759.7)					
Star DB_{t-2}	984002.7					
	(947930.2)					
Star DL_{t-2}	475560.2					
	(1186928.7)					
$Wins_{t-1}$	-26800.7	29252.4	-68389.3	38309.6	32381.0	3188.5
	(107121.3)	(98462.6)	(104010.1)	(108974.8)	(108002.9)	(107336.9)
$Wins_{t-2}$	105240.5*	144613.5**	129268.5*	144210.0*	117311.1	114024.1
	(62154.1)	(66425.7)	(67525.4)	(75426.6)	(80101.5)	(72453.8)
$CoachCareer_{t-1}$	2894797.6	1593888.0	2401403.5	1200533.5	1256494.9	1522845.0
	(2051077.1)	(1957219.9)	(2002934.8)	(2040956.1)	(2024867.2)	(2060175.3)
CoachChange	-58782.0	-16192.1	-55150.5	-12145.5	-20256.5	-31704.9
	(292807.9)	(294118.4)	(301118.6)	(304540.2)	(307027.6)	(304636.3)
$BowlGame_{t-1}$	722329.3	694577.7	873857.2*	646693.4	675347.4	720120.6
	(436796.3)	(443767.6)	(462884.6)	(457642.8)	(454049.7)	(456172.4)
L1BowlWin	-206651.2	-187959.4	-66582.0	-302569.4	-315833.4	-285164.0
	(388881.0)	(413549.1)	(382501.4)	(410367.2)	(413683.8)	(409427.2)
SOS	61314.5	29729.7	35534.6	49401.1	47400.9	51349.7
	(54809.0)	(60470.8)	(58149.0)	(58117.8)	(58254.0)	(58426.1)
TDPts		68144.8	78120.9	83385.3	83494.4	78923.6
		(83815.0)	(81707.3)	(87131.1)	(86458.3)	(85837.7)
TDYds		1044767.3	1292737.8	714811.7	754280.4	1265975.5
		(2927930.6)	(2912489.9)	(2923737.4)	(2935680.7)	(2943891.5)
TDPassYds		-1047346.8	-1295474.6	-717841.1	-756821.8	-1270048.9
		(2928554.5)	(2913457.7)	(2924896.7)	(2936819.8)	(2945113.7)
TDPassTDs		-1091752.6	-1054979.2	-1168780.8	-1191102.9	-1121070.5
		(770792.5)	(749082.5)	(755174.9)	(751124.9)	(743910.0)
TDRushYds		-1038794.0	-1287346.5	-709936.7	-749633.7	-1261770.4
		(2927774.0)	(2912188.0)	(2923612.9)	(2935630.9)	(2943829.2)
TDRushTDs		-86636.2	-68778.9	-139077.0	-124242.6	-6860.5
		(643778.4)	(626067.1)	(657717.8)	(657380.3)	(663593.9)
HistWins	11270.5	1326.6	1496.2	-2420.9	-9263.4	-6782.9
	(51132.0)	(52817.6)	(52253.8)	(53336.4)	(53902.2)	(53346.8)
HistBowls	-521435.6	-464489.7	-439494.7	-459686.2	-452940.4	-461940.3
	(368074.2)	(359064.3)	(357380.4)	(357687.1)	(354971.2)	(355114.6)
HistBowlWins	501636.9	417571.2	426305.2	427727.8	452831.3	424508.7
	(450773.7)	(436889.4)	(447415.3)	(455830.6)	(451921.4)	(440332.2)
Distance	-21716.0	-24421.3	-23668.5	-22460.6	-22041.8	-24094.7
	(16822.8)	(16568.4)	(16047.0)	(16289.5)	(16272.1)	(16464.6)
UndergradPop	-102650.5	-128413.9	-174520.3	-119192.5	-111109.3	-68576.0
	(209441.7)	(206741.0)	(208344.2)	(209422.3)	(207827.5)	(202903.2)
PerCapPI	146883.4	257749.5	265500.9	220867.2	212988.5	213644.3
	(286195.9)	(328628.3)	(318848.8)	(322632.0)	(323552.2)	(321480.4)
GrPerCapPI	-22275.7	-4719.5	-16751.0	-8338.8	-4020.3	10219.7
	(124128.7)	(125816.2)	(123405.0)	(128331.5)	(128030.5)	(128727.7)
CityPop	-11923135.7	-7057157.9	-15834654.8	-706009.7	3058621.4	-552574.7
	(26824968.4)	(32268054.1)	(28364104.5)	(31675075.3)	(32890494.5)	(32124381.9)
StatePop	-1400913.1	-242314.9	-137139.9	-79764.7	-2597.2	271169.6

	(3492057.1)	(3963926.5)	(4004886.8)	(3891568.5)	(3964285.1)	(3951960.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.790	0.783	0.788	0.780	0.781	0.782

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 45

Marginal Revenue Product of Star College Basketball Players - Wins Included. This table reports fixed effects estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	966953.5*	561750.5***	255794.2	165147.4*	276439.2	314342.4*	239950.0	261080.0*
	(491931.7)	(188740.4)	(168360.1)	(88732.0)	(191644.3)	(189002.7)	(179922.3)	(144643.1)
Stars_{t-1}	226425.3	13283.8	88317.9	-3280.9	167345.1	-1644.5	22131.5	33415.2
	(380815.1)	(285594.4)	(174900.9)	(87014.6)	(287882.3)	(224140.2)	(102344.0)	(82020.7)
Stars_{t-2}	203893.4	165585.0	205185.0	221952.9**	234977.4	108587.0	159468.7	69587.1
	(336693.0)	(218117.7)	(155300.2)	(100080.7)	(243293.3)	(199662.2)	(113475.9)	(86536.2)
Wins	16401.4***	16095.1***	16532.0***	14674.9***	17132.9***	16137.1***	17154.5***	16032.2***
	(4022.4)	(4050.8)	(4061.7)	(3968.5)	(4304.9)	(4126.2)	(4226.7)	(4179.2)
Wins_{t-1}	4748.5	4102.8	4100.7	5912.3	4171.2	4528.4	4721.5	4122.7
	(4697.1)	(4621.6)	(4668.8)	(4595.2)	(4522.4)	(4586.8)	(4724.2)	(4828.4)
Wins_{t-2}	15495.5***	14761.6***	14219.9***	10899.3**	15062.1***	14880.7***	15002.4***	14752.4***
	(4544.6)	(4571.7)	(4520.0)	(4782.4)	(4172.7)	(4291.8)	(4736.9)	(4854.2)
$\text{CoachCarTourn}_{t-1}$	53608.3***	53939.5***	53237.4***	53561.2***	53678.2***	54457.3***	54653.0***	52980.0***
	(16243.8)	(16323.8)	(16347.0)	(16315.1)	(16304.6)	(16256.2)	(16259.3)	(16376.0)
CoachCareer_{t-1}	-72663.3	-30560.9	-43597.0	-72923.5	-70991.4	-72693.8	-64191.8	-59716.8
	(295769.7)	(292317.2)	(295390.0)	(291685.5)	(293372.3)	(293534.3)	(294674.0)	(292786.1)
CoachChange	21303.7	18328.6	23666.7	21192.4	21836.9	20925.1	17639.8	17187.5
	(61326.5)	(61403.0)	(60989.1)	(61483.0)	(61618.5)	(61350.9)	(61259.9)	(61464.8)
NCAATourn_{t-1}	165630.5**	167951.2**	165258.0**	172095.1**	166695.3**	161106.1**	159724.4**	159488.4**
	(74989.6)	(74251.6)	(74014.2)	(76384.5)	(72835.6)	(74381.4)	(74244.2)	(74821.3)
Round2_{t-1}	-73105.3	-64545.4	-62367.3	-64309.2	-65697.6	-64115.5	-62807.1	-60811.1
	(126983.3)	(124158.5)	(128221.5)	(129147.1)	(128643.0)	(127160.8)	(127817.7)	(126639.0)
Sweet16_{t-1}	268201.0	262449.6	267328.5	308551.4*	284234.0	276561.4	298365.6*	286065.7*
	(173635.3)	(181712.2)	(178524.2)	(170488.4)	(178246.7)	(178620.6)	(173498.7)	(171741.4)

$Elitet8_{t-1}$	-106558.5	-108711.1	-69385.5	2207.8	-87065.8	-69938.5	-86071.3	-93301.6
	(453717.0)	(459412.9)	(473096.7)	(434909.6)	(465610.0)	(474432.6)	(451961.7)	(451327.7)
$Final4_{t-1}$	351330.9	357252.4	385537.2	398992.6	372331.3	418360.6	396717.3	394768.0
	(363656.3)	(372603.0)	(365858.7)	(379135.5)	(402738.2)	(402114.1)	(377745.2)	(377032.3)
$Final_{t-1}$	-31004.4	33779.7	-51028.4	36693.2	-112965.9	-44692.1	-23126.8	-17714.0
	(269017.4)	(338853.1)	(307084.9)	(287027.4)	(322843.0)	(344107.1)	(274565.3)	(277970.8)
$Champ_{t-1}$	1804407.2**	1954931.9***	1952856.5***	2079971.4***	1858425.7**	1853390.6**	1883220.4***	1914658.2***
	(852024.8)	(585288.6)	(657342.2)	(643846.0)	(747454.4)	(726504.3)	(618545.2)	(619006.2)
NSchlsConf	3419.9	2487.8	3225.9	4183.5	5268.2	4192.6	7060.5	5710.4
	(40489.6)	(40283.4)	(40090.1)	(40602.0)	(40177.5)	(40238.4)	(40212.9)	(40307.5)
NSchlsConfAP	-43949.2	-45507.3	-46672.0	-40075.3	-39685.4	-43315.3	-43840.1	-41422.0
	(39761.7)	(41144.6)	(40921.4)	(40815.3)	(41500.5)	(41984.2)	(40413.7)	(39998.3)
NSchlsConfTourn	862.6	513.1	59.56	-2832.3	1605.7	1610.3	1709.9	2704.3
	(39096.3)	(38838.1)	(38871.9)	(38864.5)	(39006.7)	(38770.9)	(39511.4)	(39355.3)
NSchlsConfFF	-104395.1	-99768.9	-91551.5	-91890.9	-97524.2	-99203.7	-94643.9	-94380.4
	(81984.3)	(80600.9)	(81199.2)	(83667.6)	(80585.9)	(80888.9)	(81145.0)	(80966.2)
SOS	3635.6	2691.7	2858.0	1951.1	2434.3	2164.3	2137.8	1291.0
	(12091.4)	(12059.1)	(12211.9)	(12127.1)	(12059.1)	(12025.6)	(12136.8)	(12222.4)
HistWins	-1890.8	-2059.8	-2205.8	-2478.7	-2182.4	-2145.9	-1887.2	-1882.4
	(2930.4)	(2927.4)	(2925.2)	(2945.1)	(2953.5)	(2982.9)	(2926.2)	(2933.6)
HistNCAATrn	-30751.4	-28369.8	-27395.3	-43587.4	-35616.1	-32640.8	-33161.1	-38655.7
	(58566.4)	(59741.7)	(59610.3)	(58438.7)	(59062.4)	(58883.9)	(59304.3)	(58834.5)
HistRound2	-75644.3	-55178.8	-55176.0	-65482.6	-71222.5	-74954.1	-68607.5	-71657.3
	(109898.8)	(111504.5)	(111355.5)	(111102.8)	(111143.8)	(111161.1)	(111236.5)	(111515.5)
HistSweet16	-109348.1	-110798.2	-92988.2	-63467.9	-84814.2	-78889.9	-100619.0	-104764.2
	(141491.3)	(142123.7)	(138063.4)	(134181.5)	(139171.6)	(139861.1)	(145514.9)	(145375.8)
HistElite8	132811.7	146398.0	158075.9	170779.1	135952.8	131605.7	112933.1	114534.6
	(188347.9)	(193316.9)	(194087.6)	(188281.9)	(187836.7)	(190321.0)	(193890.5)	(196082.9)
HistFinal4	277229.8	357279.0	383176.7	399495.3	304066.8	290587.7	303076.4	278903.0
	(312838.5)	(314248.9)	(314886.2)	(321911.4)	(313574.3)	(317596.8)	(323032.2)	(320433.7)
HistFinal	65092.5	201973.6	205616.7	146366.0	206075.8	195219.3	151495.7	164653.3
	(601270.3)	(585697.9)	(587330.0)	(575733.5)	(566610.0)	(569223.1)	(584343.1)	(587752.8)
HistChamp	-761925.7	-829906.6	-793943.8	-754868.5	-790988.1	-798037.6	-797728.5	-832113.6
	(846758.3)	(789728.3)	(786464.4)	(773601.1)	(775861.5)	(802985.7)	(778815.9)	(789454.9)
Distance	-1028.3	-894.8	-942.9	-1182.5	-1082.4	-1007.9	-1205.4	-1075.8

	(1538.6)	(1543.9)	(1533.3)	(1555.5)	(1568.2)	(1549.4)	(1527.0)	(1521.5)
UndergradPop	-51465.9	-49241.4	-50692.7	-47641.2	-48865.7	-47912.8	-45444.4	-46252.7
	(38075.5)	(36967.0)	(37792.9)	(38400.5)	(37508.6)	(37989.5)	(37532.9)	(37093.9)
PerCapPI	13549.5	11129.1	10495.8	3777.8	15420.3	15022.1	11228.6	11050.3
	(40711.4)	(40368.0)	(39494.8)	(39902.8)	(40113.4)	(40208.8)	(39757.1)	(40299.5)
GrPerCapPI	7657.9	9120.8	10200.8	10847.5	8239.5	9923.4	8541.1	9837.2
	(15454.6)	(15486.8)	(15375.4)	(15698.8)	(15484.6)	(15630.4)	(15421.7)	(15486.3)
CityPop	838632.4	892973.9	885192.5	844416.6	984081.3	1017251.7	795369.5	774215.2
	(1919777.3)	(1884569.5)	(1900613.0)	(1922628.1)	(1882562.4)	(1869222.3)	(1884797.4)	(1908816.8)
StatePop	-34504.8	13468.7	-9179.8	30621.3	55668.1	52754.1	23559.9	44373.3
	(431570.3)	(410095.8)	(417833.8)	(432343.8)	(423219.5)	(423250.4)	(417888.4)	(424301.9)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.672	0.672	0.671	0.674	0.670	0.671	0.670	0.671
Adjusted R^2	0.969	0.969	0.968	0.969	0.968	0.968	0.968	0.969

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 46

Marginal Revenue Product of Star College Football Players. This table reports first-difference estimates of a star football player's marginal revenue product from Model (2.3) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
ΔStars_t	948869.0***	1469685.8*	1445711.1***	779553.1***	748806.3***	750360.7***
	(349418.3)	(828796.5)	(506010.5)	(235433.4)	(225132.4)	(254279.4)
$\Delta \text{Stars}_{t-1}$	709250.0*	1649626.2**	2120098.8***	573737.5***	590639.4***	739697.0***
	(402677.7)	(674256.7)	(569801.0)	(207958.1)	(208535.9)	(223208.1)
$\Delta \text{Stars}_{t-2}$	163983.3	49332.1	194599.5	-55141.1	76767.2	220992.2
	(352823.6)	(576912.1)	(441350.4)	(156582.1)	(180291.6)	(192410.0)
ΔWins_{t-1}	-54146.5	-33695.2	-91383.2	-28327.0	-36400.5	-43853.1
	(80711.3)	(75255.9)	(83775.1)	(82789.0)	(83264.7)	(83922.2)
ΔWins_{t-2}	20750.4	36759.6	24862.7	42802.2	25832.4	11422.1
	(58634.4)	(55110.4)	(55154.6)	(61054.7)	(64107.2)	(62159.7)
$\Delta \text{CoachCareer}_{t-1}$	884195.7	430509.6	880297.2	-136643.1	-140116.1	-21058.4
	(1312309.0)	(1255639.2)	(1278001.1)	(1306426.0)	(1301108.3)	(1297892.7)
ΔCoachChange	-73262.0	-26467.6	-54643.8	-4393.0	5901.6	2825.6
	(251181.7)	(251073.2)	(241656.4)	(247955.4)	(248133.9)	(247039.7)
$\Delta \text{BowlGame}_{t-1}$	439741.8	373694.9	431727.3	371401.8	384588.8	368532.4
	(359784.3)	(352783.9)	(359075.4)	(356970.6)	(356305.0)	(356858.1)
$\Delta \text{BowlWin}_{t-1}$	-215497.7	-93293.9	-47035.8	-228514.3	-241983.2	-242143.6
	(354696.1)	(340856.9)	(325671.5)	(342739.8)	(345832.5)	(347101.1)
ΔSOS_t	27455.5	37255.0	36421.3	52637.3	52301.9	49399.7
	(48864.5)	(52187.1)	(52476.9)	(50442.0)	(50416.6)	(51039.1)
ΔTDPts_t		-1764.7	2640.5	37705.6	40245.8	37889.2
		(69707.7)	(69057.6)	(70520.5)	(71058.5)	(70989.1)
ΔTDYds_t		1541229.3	1510846.0	1168792.7	1222291.0	1247976.1
		(2104018.2)	(2091956.9)	(2096167.0)	(2103501.9)	(2124458.2)
$\Delta \text{TDPassYds}_t$		-1539497.4	-1508668.2	-1168688.1	-1222021.8	-1247752.8
		(2103651.2)	(2091728.8)	(2096283.9)	(2103566.6)	(2124552.2)
$\Delta \text{TDPassTDs}_t$		-913215.8	-879058.7	-1138818.8*	-1163441.9*	-1139000.7*
		(624718.7)	(613457.9)	(630121.0)	(637136.4)	(633583.4)
$\Delta \text{TDRushYds}_t$		-1534036.7	-1503408.4	-1162771.0	-1216373.5	-1241862.4
		(2103109.5)	(2091016.2)	(2095591.4)	(2102916.2)	(2123882.9)
$\Delta \text{TDRushTDs}_t$		-324770.9	-356404.6	-546340.6	-534016.4	-498471.1
		(497808.1)	(488928.7)	(499535.4)	(500650.3)	(496791.9)
$\Delta \text{HistWins}_t$	477.1	4820.3	8041.6	-4001.5	-2100.1	-1302.8
	(52168.7)	(57253.8)	(57092.3)	(55785.0)	(55855.2)	(55761.7)

ΔHistBowls$_t$	-429669.0	-474205.6	-456987.1	-424740.3	-429260.0	-458484.8
	(324241.9)	(331002.7)	(323843.5)	(320931.3)	(322325.8)	(324853.4)
ΔHistBowlWins$_t$	354137.7	372959.8	350225.7	462937.2	447073.5	458095.4
	(372663.6)	(361051.6)	(358653.7)	(357565.9)	(357698.0)	(355794.7)
ΔDistance$_t$	-27509.6*	-29520.7*	-32039.9**	-26164.8*	-25140.5	-24894.1
	(14851.1)	(15635.2)	(15683.3)	(15470.1)	(15580.5)	(15741.2)
ΔUndergradPop$_t$	-305926.3*	-355366.1*	-351079.5*	-311359.9*	-308788.2*	-306699.0*
	(177753.5)	(185453.5)	(186002.7)	(166927.6)	(168213.6)	(168737.4)
ΔPerCapPI$_t$	175881.2	245285.9	259355.0	237906.1	237430.8	219978.5
	(289991.6)	(305125.9)	(299039.0)	(303836.3)	(303764.8)	(299368.6)
ΔGrPerCapPI$_t$	-3727.7	7836.6	1401.2	-11569.6	-8007.5	2029.2
	(106066.3)	(104850.2)	(104294.6)	(109688.7)	(109104.4)	(107490.6)
ΔCityPop$_t$	28054638.2	16664412.0	14035656.0	18365911.2	18833592.2	16952734.7
	(23269063.7)	(23092406.6)	(22175343.5)	(23958552.0)	(23516072.6)	(23040343.3)
ΔStatePop$_t$	-1215251.8	-650802.3	-859168.4	-1058134.8	-1029541.7	-787390.3
	(2801694.5)	(2778169.5)	(2812999.1)	(2745399.2)	(2809285.5)	(2786095.6)
ΔConference	216108.4	187016.2	148304.5	222704.3	219111.6	209820.7
	(231504.8)	(217321.0)	(223844.3)	(224161.5)	(230133.0)	(232429.1)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	936	936	936	936	936	936
R^2	0.145	0.155	0.169	0.168	0.165	0.162

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 47

Marginal Revenue Product of Star College Basketball Players. This table reports first-difference estimates of a star basketballl player's marginal revenue product from Model (2.3) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers and, (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔStars_t	1244669.4***	682364.7***	332745.2	197634.8**	475602.4**	435118.6**	369001.0*	395939.8**
	(473789.8)	(152435.6)	(204309.7)	(90979.0)	(188524.0)	(174028.1)	(204126.7)	(162427.6)
ΔStars_{t-1}	1316327.3***	355506.6*	157342.8	53072.7	328429.3	271346.3	129652.0	177974.9*
	(339865.8)	(197409.3)	(157492.2)	(87034.0)	(254837.0)	(187689.1)	(123510.3)	(104788.6)
ΔStars_{t-2}	605049.6	270524.5	37812.9	197711.5**	125740.9	34561.9	111437.7	102171.0
	(369234.7)	(188809.1)	(159556.9)	(99526.1)	(231342.9)	(200534.0)	(115025.0)	(96238.5)
ΔWins_{t-1}	-1301.9	-1603.7	-934.6	1277.0	-763.9	-1028.1	-407.9	-1202.9
	(4706.4)	(4601.7)	(4711.0)	(4571.6)	(4688.1)	(4743.9)	(4704.1)	(4713.2)
ΔWins_{t-2}	6140.3	5933.1	7128.9	4308.6	7100.3	7057.4	6653.0	5910.6
	(5056.1)	(4980.6)	(5098.9)	(5349.8)	(5149.0)	(5205.0)	(5239.5)	(5090.4)
$\Delta\text{CoachCarTourn}_{t-1}$	33305.8*	33326.3*	34080.3*	34753.3*	33151.4*	33005.1*	33498.5*	33115.2*
	(18660.4)	(18780.8)	(18727.3)	(18652.8)	(18535.2)	(18281.2)	(18778.8)	(18692.8)
$\Delta\text{CoachCareer}_{t-1}$	262163.2	295546.3	270967.0	183813.2	236739.8	253957.1	265972.6	270420.7
	(259980.7)	(258929.2)	(264018.8)	(257315.3)	(260180.0)	(260983.4)	(257039.7)	(256011.5)
$\Delta\text{CoachChange}_t$	-4611.6	-6869.6	-4689.7	-4844.7	-5278.7	-4711.1	-8270.4	-9081.9
	(54886.6)	(54844.0)	(54889.6)	(54770.4)	(54771.8)	(54472.8)	(54813.7)	(55005.8)
$\Delta\text{NCAATourn}_{t-1}$	74719.7	74675.0	67046.6	70089.8	68273.4	61816.5	69830.1	64272.1
	(68202.2)	(67167.5)	(66767.5)	(68009.1)	(67868.5)	(69181.8)	(68045.5)	(67700.6)
$\Delta\text{Round2}_{t-1}$	-85080.5	-85634.6	-78693.5	-76779.6	-80149.4	-82603.7	-74958.7	-75548.6
	(103244.2)	(102833.0)	(104510.7)	(106486.2)	(104118.6)	(104476.9)	(103440.2)	(102373.0)
$\Delta\text{Sweet16}_{t-1}$	95587.9	119129.6	118149.8	168226.7	119035.8	118929.7	162602.3	141597.7
	(118749.5)	(126224.0)	(126882.1)	(121669.4)	(127498.6)	(125137.8)	(124654.8)	(123438.1)
$\Delta\text{Elite8}_{t-1}$	-313071.5	-292302.4	-258628.3	-179807.7	-279848.1	-299177.7	-303678.9	-303212.8
	(337691.0)	(339913.1)	(342523.1)	(322040.4)	(340484.4)	(345180.8)	(334222.0)	(335192.5)

ΔFinal4$_{t-1}$	-219095.3	-170690.6	-195919.7	-210148.5	-230657.8	-224554.6	-154629.5	-160398.5
	(403620.2)	(412452.1)	(387443.2)	(403956.8)	(425532.7)	(420284.7)	(408967.9)	(407983.0)
ΔFinal$_{t-1}$	-20853.5	72935.7	-22729.9	111227.5	1639.0	-16337.9	12868.9	33950.7
	(258131.2)	(334494.6)	(310338.5)	(222601.8)	(261274.0)	(268731.4)	(267721.0)	(275527.2)
ΔWinner$_{t-1}$	515218.4	1121796.8***	1015056.5**	1308687.3***	943865.2**	847829.4*	1039990.5**	1067729.4**
	(489234.2)	(393829.8)	(433272.2)	(352109.5)	(450760.4)	(479111.8)	(413073.1)	(423185.6)
ΔNSchlsConf$_t$	43502.9	41396.7	39349.8	46093.3	42205.8	39228.4	46549.1	43871.9
	(46441.1)	(46218.8)	(46566.7)	(46286.6)	(45887.1)	(46334.5)	(46441.6)	(45467.9)
ΔNSchlsConfAP$_t$	-13052.3	-15469.7	-18245.2	-8652.0	-13483.5	-12887.4	-14829.5	-12345.1
	(46963.1)	(48238.3)	(48605.9)	(49411.1)	(48440.7)	(48940.4)	(47794.7)	(46554.3)
ΔNSchlsConfTourn$_t$	-12350.8	-12946.5	-9729.0	-16912.5	-8889.4	-9493.0	-11588.6	-10277.3
	(45308.9)	(45319.5)	(45403.0)	(44873.6)	(45066.1)	(44871.2)	(45610.7)	(45345.5)
ΔNSchlsConfFF$_t$	-57304.9	-56821.6	-56589.0	-60358.2	-60979.0	-61468.1	-57036.6	-59452.5
	(63766.9)	(62216.7)	(63476.0)	(64899.7)	(62150.1)	(61644.2)	(61963.9)	(61862.0)
ΔSOS$_{t-1}$	13187.2	12593.2	13027.8	11312.8	12107.4	12144.1	12113.7	11368.7
	(9932.5)	(9907.4)	(10032.1)	(10025.9)	(9938.5)	(10085.9)	(9959.7)	(9960.6)
ΔHistWins$_t$	-6248.3**	-6076.0**	-6260.4**	-6379.7**	-6408.1**	-6509.8**	-6419.0**	-5988.2*
	(3096.3)	(3070.5)	(3114.8)	(3093.3)	(3148.6)	(3169.9)	(3105.8)	(3075.6)
ΔHistNCAATrn$_t$	14157.4	15811.5	19392.1	17058.6	16445.2	20267.4	18377.4	14935.6
	(65658.1)	(66096.7)	(65211.2)	(65551.6)	(65702.3)	(65453.8)	(66087.2)	(65878.3)
ΔHistRnd2$_t$	-32880.5	-15504.0	-13549.5	-19867.8	-25276.1	-25021.1	-13155.0	-19326.6
	(130537.3)	(129231.4)	(131319.9)	(127476.7)	(131509.0)	(131654.6)	(131030.2)	(131018.2)
ΔHistSwt16$_t$	24887.9	38188.8	34712.4	56581.1	59016.0	71304.5	44849.9	35880.7
	(136107.5)	(138638.7)	(138781.2)	(133537.2)	(135459.6)	(140942.6)	(139387.9)	(131827.6)
ΔHistElite8$_t$	-58198.2	-67712.9	-83369.0	-47078.2	-68912.9	-79856.8	-102662.3	-94145.5
	(146252.2)	(147578.3)	(152915.5)	(145376.3)	(147409.8)	(148945.9)	(151412.6)	(153192.8)
ΔHistFin4$_t$	282957.6	346493.3	305677.5	432115.7	248681.7	239408.4	298909.8	281965.4
	(305170.3)	(315927.5)	(312649.5)	(319617.8)	(298725.9)	(304325.5)	(308255.6)	(308102.1)
ΔHistFinal$_t$	-339759.5	-160841.0	-228586.7	-195778.1	-200579.6	-247918.7	-193488.7	-206363.6
	(384959.2)	(347211.1)	(369356.3)	(378611.7)	(365343.3)	(355409.6)	(368204.7)	(355766.8)
ΔHistWinner$_t$	-755366.8	-864673.7	-787832.7	-768445.5	-739792.4	-767086.0	-772197.9	-836478.2
	(909030.1)	(941372.5)	(938316.7)	(918507.9)	(941995.7)	(928306.1)	(926269.9)	(918290.0)
ΔDistance$_t$	-537.6	-555.9	-587.1	-798.1	-643.4	-542.7	-792.7	-781.2
	(1589.6)	(1635.2)	(1584.8)	(1625.6)	(1615.3)	(1609.3)	(1593.6)	(1605.8)
ΔUndergradPop$_t$	-55936.6	-58120.0*	-51045.9	-51872.6	-54945.6	-53246.9	-46710.5	-49400.2

	(36042.9)	(34025.1)	(35180.4)	(34385.2)	(33696.1)	(34348.9)	(35373.6)	(32964.8)
ΔPerCapPI$_t$	33400.8	30174.2	31512.5	23621.3	34446.1	37192.6	31129.1	32844.3
	(37742.9)	(36756.3)	(37080.4)	(37450.6)	(37712.5)	(37465.6)	(37433.7)	(36809.1)
ΔGrPerCapPI$_t$	15075.3	16015.3	17198.2	19420.4	15033.4	16145.8	15763.7	15988.7
	(14224.1)	(14449.2)	(14469.3)	(14358.1)	(14119.5)	(14138.6)	(14317.5)	(14249.5)
ΔCityPop$_t$	810717.9	890468.9	845822.9	814232.8	1080732.3	1069248.4	602207.3	585040.1
	(1761651.3)	(1735986.2)	(1726862.9)	(1681573.7)	(1703770.9)	(1716922.6)	(1692809.1)	(1687281.1)
ΔStatePop$_t$	95573.2	249783.1	269071.9	287891.1	290827.5	281120.3	274095.2	291216.1
	(379218.7)	(344333.9)	(353527.4)	(363255.5)	(352489.5)	(354104.0)	(353083.6)	(357574.8)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2819	2819	2819	2819	2819	2819	2819	2819
R^2	0.103	0.0990	0.0951	0.106	0.0950	0.0967	0.0952	0.100

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 48

Marginal Revenue Product of Star College Football Players. This table reports OLS estimates of a star football player's marginal revenue product from Model (2.4) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	1079047.5***	1238360.9	1133259.8*	688562.2***	682939.7***	653164.6***
	(289289.4)	(896004.8)	(578029.1)	(215182.7)	(207103.7)	(236700.4)
Stars_{t-1}	231460.8	538886.5	1058006.7**	279846.5	280493.5	407705.1**
	(397490.4)	(665666.7)	(523856.6)	(227686.1)	(209903.5)	(198800.1)
Stars_{t-2}	256403.5	-948961.4*	-1106412.0**	-279814.4	-191538.5	-149343.2
	(361902.0)	(510459.2)	(524545.0)	(219815.8)	(217130.7)	(208955.2)
Revenues_{t-1}	0.634***	0.632***	0.634***	0.631***	0.629***	0.629***
	(0.0518)	(0.0469)	(0.0466)	(0.0463)	(0.0465)	(0.0468)
Revenues_{t-2}	0.0682	0.0772	0.0802	0.0779	0.0783	0.0789
	(0.0633)	(0.0603)	(0.0600)	(0.0604)	(0.0602)	(0.0604)
Wins_{t-1}	-14847.2	-862.0	-55154.9	-14746.7	-18032.2	-22011.3
	(99422.4)	(98353.1)	(104678.3)	(103253.5)	(102582.5)	(104112.3)
Wins_{t-2}	-77429.7	-41513.6	-27225.5	-33286.2	-41261.8	-53439.4
	(56617.1)	(58860.2)	(59779.5)	(68664.5)	(69703.1)	(66024.5)
CoachCareer_{t-1}	1715688.8	1517318.8	1618001.6	925489.1	929471.6	1089903.8
	(1512631.9)	(1409909.3)	(1397621.8)	(1414940.7)	(1412892.8)	(1403736.1)
CoachChange	-95462.1	-66663.3	-77862.1	-51784.0	-28522.2	-32981.2
	(337630.7)	(352351.2)	(345736.8)	(345418.0)	(344997.4)	(342469.0)
BowlGame_{t-1}	-687927.9	-756760.7	-672961.4	-788983.7	-775863.1	-772709.5
	(475596.6)	(466738.1)	(472307.6)	(475429.3)	(468414.4)	(469621.9)
BowlWin_{t-1}	288046.4	400718.0	458361.7	351149.8	326236.1	309829.1
	(393782.9)	(390772.7)	(379398.1)	(389794.5)	(393323.1)	(396806.5)
SOS	51809.1	58921.8	58962.0	73413.7	74622.0	70219.9
	(57004.3)	(57313.8)	(58992.9)	(59515.3)	(59211.3)	(58987.1)
TDPts		-30825.8	-22234.3	-9301.5	-1996.3	-4059.2
		(85977.6)	(85755.9)	(83582.6)	(83820.1)	(83620.2)
TDYds		376665.3	380610.4	247775.3	330994.5	293402.8
		(3186572.5)	(3209443.1)	(3226591.8)	(3218781.3)	(3220367.3)
TDPassYds		-369597.3	-373845.8	-243323.0	-326252.1	-288229.1
		(3186568.2)	(3209592.7)	(3226908.6)	(3219044.5)	(3220573.8)
TDPassTDs		-820347.3	-836225.0	-973055.8	-1037798.0	-1015333.0
		(721809.2)	(712863.6)	(709903.2)	(716561.5)	(712744.3)
TDRushYds		-367740.3	-371835.3	-239840.2	-323314.4	-285408.0
		(3187225.1)	(3210032.9)	(3227510.5)	(3219736.8)	(3221238.5)

TDRushTDs		-101315.3	-179351.9	-185732.9	-207994.5	-185822.5
		(660016.3)	(666941.3)	(636734.7)	(638233.7)	(633879.0)
HistWins	30915.3	20417.2	18211.6	14585.9	14962.8	14834.6
	(37546.8)	(37860.7)	(37779.8)	(36976.7)	(37145.9)	(37289.6)
HistBowls	-554841.7**	-560824.3**	-555038.6**	-496530.3**	-502466.8**	-515950.2**
	(260390.5)	(255401.8)	(256815.4)	(249715.7)	(249787.9)	(251578.2)
HistBowlWins	-109935.1	-52253.8	-40695.2	-24408.0	-17567.1	-22140.1
	(326160.7)	(310007.7)	(308163.2)	(314767.6)	(319018.1)	(320639.3)
Distance	-3256.2	-3500.2	-2536.3	-4478.5	-4221.5	-4335.6
	(10022.0)	(9673.9)	(9746.8)	(10060.9)	(10001.4)	(9875.2)
UndergradPop	1988.1	-12161.5	-14228.9	-21101.1	-27141.8	-26943.7
	(97804.0)	(103585.6)	(103399.0)	(103480.7)	(103954.5)	(104028.7)
PerCapPI	52178.7	66961.2	76344.3	80875.7	75583.5	71641.2
	(141963.3)	(137297.4)	(135854.6)	(139639.8)	(139588.3)	(139017.6)
GrPerCapPI	40208.4	44195.0	43275.8	19036.3	23879.7	30274.8
	(100621.3)	(100180.3)	(99411.9)	(100907.6)	(100474.7)	(100463.8)
CityPop	14690061.1	10350327.0	8011106.6	9461579.5	9401550.8	9344938.5
	(12124261.1)	(12335007.7)	(12749482.5)	(12343110.3)	(12313243.0)	(12434151.0)
StatePop	177521.1	194540.6	248217.4	174234.3	159525.0	143899.3
	(358162.7)	(362490.7)	(369669.9)	(370581.2)	(372859.6)	(375933.4)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
R^2	0.972	0.972	0.972	0.972	0.972	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 49

Marginal Revenue Product of Star College Basketball Players. This table reports OLS estimates of a star basketball player's marginal revenue product from Model (2.4) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1206300.1**	635196.1**	341945.7	247469.1**	527306.9**	421527.9*	414020.6**	370848.7**
	(501780.2)	(245445.2)	(212881.3)	(99151.5)	(236665.1)	(254394.8)	(190465.1)	(155549.9)
Stars_{t-1}	462913.2	54083.6	-19918.0	-38558.9	198894.2	17053.7	-42974.3	-10924.1
	(315212.3)	(279577.9)	(189781.5)	(88269.1)	(325219.3)	(246099.5)	(126430.0)	(78065.5)
Stars_{t-2}	-413247.1	26767.6	-50709.7	164020.0*	-59523.1	-168030.2	8130.3	-91041.0
	(362317.1)	(227605.2)	(213869.0)	(98863.0)	(369112.6)	(261677.2)	(194254.3)	(120111.6)
Revenues_{t-1}	0.448***	0.441***	0.441***	0.439***	0.441***	0.442***	0.441***	0.443***
	(0.0823)	(0.0813)	(0.0816)	(0.0813)	(0.0816)	(0.0818)	(0.0814)	(0.0813)
Revenues_{t-2}	0.192***	0.193***	0.190***	0.185***	0.190***	0.189***	0.189***	0.189***
	(0.0297)	(0.0290)	(0.0291)	(0.0293)	(0.0301)	(0.0299)	(0.0293)	(0.0293)
Wins_{t-1}	6011.0	5756.8	6123.9	7507.6*	6079.7	5911.1	6474.5	5223.1
	(4261.9)	(4412.6)	(4470.7)	(4181.1)	(4291.2)	(4306.0)	(4334.6)	(4433.7)
Wins_{t-2}	8202.0*	6776.9	7673.1	3817.7	7985.6*	8356.2*	6720.7	7482.8
	(4754.0)	(4513.5)	(4702.4)	(4466.6)	(4315.5)	(4515.0)	(4753.7)	(4855.8)
$\text{CoachCarTourn}_{t-1}$	44632.1**	43999.3**	44541.0**	43340.3**	45355.4**	44480.5**	44033.6**	44079.1**
	(19463.0)	(19894.6)	(20074.0)	(20158.1)	(19608.0)	(19728.9)	(19540.5)	(19713.0)
CoachCareer_{t-1}	-186613.9	-135308.9	-145741.7	-134982.8	-185301.1	-156790.9	-133499.5	-106543.8
	(288071.0)	(289959.1)	(296798.2)	(291648.2)	(288015.8)	(291108.2)	(287163.3)	(284059.0)
CoachChange	-13247.6	-11962.3	-10224.8	-5233.5	-11763.5	-11399.0	-15070.8	-13199.0
	(68897.7)	(68803.0)	(68826.9)	(68953.7)	(69037.2)	(68553.2)	(68938.2)	(69266.6)
NCAATourn_{t-1}	115584.5	120983.6	110093.5	108834.6	110537.4	100205.7	112591.4	109957.2
	(81227.7)	(80445.5)	(80642.3)	(83139.0)	(81157.3)	(82190.2)	(80798.3)	(80977.8)
Round2_{t-1}	-164543.6	-150598.0	-151782.0	-160243.5	-146019.8	-152483.0	-143364.9	-141868.2
	(129270.4)	(126884.6)	(126975.1)	(129578.2)	(128882.0)	(127360.3)	(128413.8)	(128374.6)

Sweet16$_{t-1}$	445793.1***	419172.0**	427315.2**	465840.0***	426405.7**	427571.5**	477195.9***	450454.4***
	(165884.8)	(173351.1)	(166647.8)	(164354.3)	(166727.8)	(167560.5)	(163760.6)	(163199.3)
Elite8$_{t-1}$	-10392.7	14934.9	93325.4	112250.4	33918.8	38258.1	50490.7	26337.4
	(385419.6)	(390238.5)	(387504.4)	(356189.2)	(383041.2)	(391301.9)	(383554.1)	(377051.0)
Final4$_{t-1}$	-57227.5	13557.5	59427.7	8286.0	-10943.9	60890.5	80826.5	62259.4
	(421818.6)	(446281.2)	(429546.8)	(430123.2)	(460996.2)	(460609.7)	(452564.4)	(455293.6)
Final$_{t-1}$	-300987.7	-247369.9	-299080.4	-235792.1	-340469.2	-290243.9	-245262.2	-232758.4
	(350685.4)	(376541.0)	(356213.1)	(359965.2)	(353018.6)	(360152.7)	(340895.3)	(344554.2)
Winner$_{t-1}$	1297594.2	1663255.5**	1607968.5**	1747320.4**	1487041.1*	1420246.4*	1648517.3**	1672243.8**
	(849166.7)	(695375.0)	(712887.6)	(738563.8)	(820233.7)	(834295.7)	(695408.9)	(691206.4)
NSchlsConf	27822.9	29991.8	29914.8	32539.3	30691.9	29324.8	32909.2	31387.2
	(31629.0)	(31709.3)	(31826.6)	(31790.5)	(31540.6)	(31734.9)	(32136.8)	(31784.6)
NSchlsConfAP	22454.7	15360.0	14727.9	24797.3	20556.7	18865.2	19203.0	19769.4
	(56494.3)	(58410.2)	(58432.3)	(59055.3)	(59834.8)	(59595.1)	(58948.2)	(58101.1)
NSchlsConfTourn	28202.0	30175.6	31082.3	20921.7	32437.7	30782.6	29549.7	30898.2
	(48003.6)	(48410.3)	(48639.3)	(48410.4)	(48064.3)	(48282.7)	(48824.9)	(49039.3)
NSchlsConfFF	-36140.8	-27923.7	-21836.2	-26704.9	-31000.8	-30224.3	-21458.4	-23343.0
	(68650.8)	(68877.3)	(69733.7)	(68920.6)	(67538.7)	(67163.0)	(68215.0)	(67792.8)
SOS	13337.5	12274.2	12781.6	11714.9	11902.6	11967.7	11678.8	10914.9
	(11787.8)	(11907.9)	(11979.5)	(12003.8)	(11898.9)	(11886.5)	(11991.5)	(12044.2)
HistWins	101.8	-56.41	-33.10	-22.15	-63.17	-12.25	-68.71	201.0
	(1929.2)	(1915.4)	(1954.4)	(1911.9)	(1941.3)	(1976.4)	(1969.3)	(1939.0)
HistNCAATourn	-53565.8	-54934.7	-56008.6	-62778.2	-57725.7	-57067.0	-57452.6	-60085.8
	(45451.5)	(46243.4)	(45414.1)	(46404.5)	(46614.8)	(47194.7)	(46097.8)	(45931.2)
HistRound2	21720.0	30445.9	37104.7	26629.5	25622.1	24147.9	33372.2	32558.6
	(80744.7)	(82476.3)	(86308.0)	(83036.3)	(82043.8)	(82092.4)	(83584.2)	(83175.1)
HistSweet16	-20948.5	643.0	1899.6	39178.8	19471.0	16897.8	2004.0	-703.5
	(128013.4)	(137708.6)	(136452.6)	(128342.4)	(121424.7)	(117290.1)	(137979.0)	(135976.4)
HistElite8	45765.9	50387.4	43036.8	51390.3	32674.4	31669.0	25604.2	28053.2
	(133967.0)	(136052.8)	(133963.6)	(133829.8)	(133475.4)	(132064.9)	(131072.0)	(132264.4)
HistFinal4	431610.9	520572.6	479226.8	531320.8	438941.5	438856.3	476489.6	452650.3
	(316134.2)	(315784.0)	(328219.2)	(330413.6)	(331864.7)	(326186.2)	(318149.3)	(315675.3)
HistFinal	-1068049.1**	-953288.7**	-924933.0**	-895721.7*	-867513.9*	-909060.1**	-955645.0**	-975649.9**
	(465705.0)	(445241.6)	(449436.9)	(462139.6)	(459266.3)	(455122.4)	(433085.5)	(438775.0)
HistWinner	-622707.1	-633117.7	-657391.7	-596307.2	-639083.6	-691910.3*	-639940.2	-678648.0*

	(411160.2)	(414867.8)	(403935.0)	(398700.7)	(421273.8)	(415081.1)	(396892.8)	(390302.8)
Distance	-2321.8	-2184.2	-2354.5	-2309.5	-2377.4	-2428.4	-2353.1	-2349.4
	(1509.1)	(1543.4)	(1497.7)	(1547.4)	(1535.9)	(1517.5)	(1514.7)	(1503.8)
UndergradPop	950.5	1459.5	3002.9	4046.8	1847.1	2877.6	3848.0	3755.5
	(14195.6)	(13949.0)	(14735.0)	(14831.3)	(14285.8)	(14971.4)	(14797.3)	(14022.5)
PerCapPI	-23875.3	-23996.7	-25879.5	-26487.4	-23514.8	-23564.2	-23918.8	-23726.5
	(22653.2)	(23478.6)	(23435.4)	(22946.4)	(22908.5)	(22930.6)	(22545.1)	(23328.4)
GrPerCapPI	22062.7	22657.7	23895.3	24645.1	22503.1	24007.5	22923.0	23037.0
	(14613.8)	(14803.8)	(15089.2)	(15086.1)	(15111.5)	(15106.0)	(14991.9)	(15024.3)
CityPop	1267825.9	1251383.2	1293222.0	1206210.7	1323921.0	1329166.8	1250995.7	1272407.6
	(855346.9)	(848467.6)	(847420.6)	(839509.0)	(842134.5)	(848038.5)	(851817.9)	(847076.3)
StatePop	-95560.3	-90816.2	-97540.3*	-104757.4*	-99733.3*	-97209.7	-99716.7*	-98358.2*
	(59285.8)	(58174.8)	(58981.9)	(58671.4)	(60255.3)	(60474.5)	(59292.9)	(57900.0)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
R^2	0.963	0.963	0.963	0.963	0.963	0.963	0.963	0.963

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 50

Marginal Revenue Product of Star College Basketball Players at Schools With Division 1 FBS Programs. This table reports fixed effects estimates of a star basketball player's marginal revenue product from Model (2.1) on the subset of schools that also have a Division 1 FBS football program over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stars	1114532.9**	707635.5***	375421.7*	234764.9**	367265.6*	394478.2*	505290.1**	407254.8**
	(551453.9)	(212897.4)	(191674.2)	(103653.3)	(190847.6)	(208448.9)	(238299.5)	(203111.9)
Stars_{t-1}	104860.9	32287.0	113548.0	-12997.5	251296.3	-16303.1	130230.0	94249.4
	(455975.9)	(340511.3)	(213514.4)	(108401.2)	(321824.0)	(260249.4)	(148243.0)	(134762.3)
Stars_{t-2}	150825.9	160804.2	247456.9	234387.1**	300116.0	111073.8	124997.9	-3839.7
	(387708.2)	(245773.4)	(189350.9)	(117911.1)	(236329.2)	(210690.6)	(152950.6)	(133744.6)
Wins_{t-1}	12154.8	10160.2	10750.6	15136.5	10211.4	11411.3	10771.6	11238.3
	(11816.8)	(11670.9)	(11931.7)	(11751.4)	(11609.2)	(11671.5)	(12034.0)	(12206.7)
Wins_{t-2}	21788.9**	19898.4**	18709.4*	13020.9	19679.9**	20551.7**	19042.6*	24763.4**
	(9552.0)	(9880.7)	(10015.8)	(10982.6)	(9275.3)	(9732.1)	(10592.7)	(10784.8)
$\text{CoachCarTourn}_{t-1}$	51009.4***	51767.4***	51052.1**	52421.2***	52211.4***	53427.2***	49956.9**	52697.7***
	(19438.7)	(19446.2)	(19578.9)	(19398.8)	(19642.8)	(19506.6)	(19720.0)	(19559.4)
CoachCareer_{t-1}	467654.1	572089.0	515476.9	450088.1	460972.5	474254.7	506618.6	478221.6
	(793992.9)	(785786.8)	(798968.9)	(794863.0)	(797211.6)	(798979.0)	(790794.5)	(779719.6)
CoachChange	28324.9	20682.5	39182.2	32091.6	26958.0	27224.5	16675.0	24523.1
	(150820.8)	(150872.2)	(150140.8)	(151659.0)	(151426.9)	(150583.0)	(151181.8)	(150388.1)
NCAATourn_{t-1}	266317.1*	270618.4**	259113.4*	266463.9*	264986.5**	252185.6*	273269.3**	240664.6*
	(135093.2)	(133685.7)	(133819.4)	(136466.6)	(130821.9)	(135882.6)	(133577.5)	(134010.9)
Round2_{t-1}	-56943.3	-42232.2	-43396.7	-64286.0	-44760.7	-42026.0	-32585.4	-54558.7
	(189833.9)	(188802.7)	(195067.4)	(193804.0)	(193160.1)	(190874.0)	(188410.3)	(191329.1)
Sweet16_{t-1}	322257.1	316975.5	306076.0	373163.6	345566.1	332514.7	354051.8	338248.3
	(251965.7)	(261671.7)	(258920.6)	(247710.5)	(257849.7)	(255575.3)	(252629.5)	(251137.4)
Elitet8_{t-1}	-153198.0	-130213.7	-80153.7	-37801.3	-120363.5	-76703.7	-125195.1	-108277.4

	(530757.9)	(530574.6)	(540611.9)	(517744.0)	(551028.8)	(554340.0)	(520071.6)	(529136.4)
Final4_{t-1}	406411.0	459061.9	454975.2	396057.6	437395.7	508797.3	439610.9	432551.5
	(475356.1)	(476840.8)	(468096.5)	(504943.7)	(528058.7)	(520541.9)	(487029.1)	(473471.8)
Final_{t-1}	-230925.4	-122765.8	-249438.2	-163529.0	-346225.4	-240376.9	-204145.3	-244965.1
	(342458.8)	(451213.3)	(383082.9)	(378637.8)	(403089.1)	(415502.9)	(354405.3)	(330940.6)
Champ_{t-1}	1842348.1*	1895952.4***	1888025.9***	2004486.5***	1749210.4**	1758590.7**	1841494.2***	1718239.4***
	(964111.2)	(632171.8)	(719208.1)	(705646.0)	(834333.3)	(808820.0)	(681780.7)	(608902.7)
NSchlsConf	69494.6	72098.3	75743.2	75450.8	75697.5	72469.5	68573.7	60506.3
	(91282.2)	(91147.6)	(91318.6)	(92675.5)	(90957.3)	(90998.7)	(91490.3)	(91469.7)
NSchlsConfAP	-7815.9	-8770.7	-11758.8	-3693.9	1029.6	-5423.5	683.2	-5564.6
	(51896.6)	(53469.5)	(52947.0)	(53218.8)	(54304.4)	(55569.0)	(51960.0)	(53398.4)
NSchlsConfTourn	-983.4	-1375.1	-2296.0	-11265.5	-1211.5	-574.7	-1172.9	3756.6
	(55710.6)	(54999.8)	(55140.3)	(55358.9)	(55193.4)	(54791.9)	(56924.3)	(56164.3)
NSchlsConfFF	-129228.1	-120836.3	-110797.4	-106437.9	-116672.4	-120829.1	-115340.6	-127809.3
	(92046.1)	(91145.2)	(90939.4)	(94537.5)	(90295.1)	(91367.4)	(90724.8)	(89948.1)
SOS	11467.5	7362.0	9025.0	5291.1	6830.0	6016.8	6930.8	7024.4
	(33072.5)	(33264.4)	(33527.1)	(33337.6)	(33310.2)	(33112.0)	(33199.5)	(33378.9)
HistWins	-9424.4	-9713.8	-10401.3	-10403.5	-10574.2	-9871.3	-10580.0	-8451.6
	(7028.5)	(6980.1)	(6968.6)	(6875.4)	(7084.4)	(7135.8)	(7118.7)	(7074.0)
HistNCAATrn	-25166.4	-33732.8	-27954.5	-66065.7	-36879.5	-32679.2	-52902.2	-56483.6
	(126454.7)	(128802.7)	(125829.9)	(124589.8)	(127620.6)	(126624.5)	(125681.0)	(124777.4)
HistRound2	64195.4	84287.3	92310.1	72440.0	82163.7	66529.7	84180.0	85653.9
	(148610.4)	(150974.6)	(150891.0)	(153221.0)	(153594.6)	(152179.6)	(153531.8)	(156400.1)
HistSweet16	-21679.0	-31544.9	-11948.0	16898.5	8811.3	5419.2	-19566.8	-37108.0
	(174757.2)	(176368.8)	(170345.0)	(166193.9)	(172502.7)	(176390.9)	(181140.4)	(177234.8)
HistElite8	203838.5	234248.3	246010.3	240327.5	218886.8	202919.2	198824.2	159471.1
	(217905.3)	(227847.5)	(228047.5)	(214120.9)	(219623.8)	(221931.7)	(230552.5)	(230544.5)
HistFinal4	237281.9	339847.6	388352.6	350177.0	280456.0	251142.8	264863.7	217503.7
	(315338.5)	(334806.4)	(330441.7)	(328198.8)	(325830.1)	(331158.4)	(343121.0)	(321177.6)
HistFinal	173366.6	314995.0	329923.2	224499.1	335478.5	310589.7	304178.9	216906.6
	(598644.0)	(585211.7)	(585669.4)	(568731.3)	(559107.1)	(563603.5)	(591517.6)	(607001.4)
HistChamp	-684621.1	-751687.2	-704615.5	-670633.7	-685337.4	-709848.6	-740033.5	-727526.0
	(897664.5)	(836951.5)	(831011.2)	(816167.6)	(821086.6)	(847529.8)	(834396.2)	(807876.3)
Distance	-944.2	-724.4	-897.0	-817.3	-1083.7	-972.4	-741.9	-1208.4
	(4392.0)	(4420.9)	(4372.9)	(4389.2)	(4499.1)	(4459.4)	(4375.0)	(4421.1)

UndergradPop	-27995.3	-27031.3	-29701.6	-22686.7	-24773.9	-22541.3	-14464.6	-33090.4
	(55132.5)	(53425.0)	(54700.5)	(54545.6)	(54311.1)	(55193.1)	(53506.8)	(54929.7)
PerCapPI	51620.5	45285.6	45682.7	34633.9	50462.3	50194.6	49149.9	48540.3
	(76495.5)	(75133.7)	(73032.6)	(74317.1)	(74856.1)	(74506.3)	(76114.4)	(75626.1)
GrPerCapPI	22156.6	27596.5	29149.2	30568.1	26176.8	29169.3	29526.0	26837.0
	(29242.8)	(29204.3)	(29270.5)	(29384.9)	(29189.2)	(29436.0)	(29454.9)	(28576.9)
CityPop	-4969357.8	-4646198.4	-4880432.6	-4663065.5	-3987118.6	-3812831.7	-5683805.4	-4384222.2
	(4726563.4)	(4375639.7)	(4490119.7)	(4409855.4)	(4007287.1)	(3984494.3)	(4785989.6)	(4391061.3)
StatePop	164476.3	322829.7	258785.1	371388.0	406174.1	391414.9	369963.8	449593.8
	(961606.1)	(897004.5)	(923547.7)	(959991.6)	(937911.7)	(937879.3)	(968491.0)	(951488.5)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1190	1190	1190	1190	1190	1190	1190	1190
Within R^2	0.686	0.686	0.685	0.690	0.685	0.685	0.687	0.688
Adjusted R^2	0.957	0.957	0.957	0.958	0.957	0.957	0.958	0.958

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 51

Marginal Revenue Product of Ex-Ante Star College Football Players. This table reports fixed effects estimates of an ex-ante star football player's marginal revenue product from Model (2.1) over the sample period 2005-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) Top Rivals.com Recruits (Rivals.com rating of 6.1), (2) High Rivals.com Recruits (Rivals.com rating of 6 or better), (3) Rivals.com Five Star Rated Recruit. The last three measures (4-6) are the same as (1-3) except isolated to only the Offensive Positions (OP) of Quarterback, Running Back, and Wide Receiver.

	(1) Top Riv	(2) High Riv	(3) 5 Star	(4) Top Riv OP	(5) High Riv OP	(6) 5 Star OP
Stars	291572.2	100964.3	452130.7	844171.8	208951.9	829356.5
	(475612.5)	(258900.2)	(489486.5)	(735283.7)	(515711.0)	(739502.1)
Stars_{t-1}	88005.2	-238273.1	447989.4	-478993.5	-315699.6	-366974.8
	(359552.0)	(263211.1)	(287902.5)	(422948.6)	(293817.5)	(405187.3)
Stars_{t-2}	477074.7	437018.8	138076.7	174979.9	638371.0	-227883.6
	(652932.0)	(388483.6)	(505997.3)	(794618.4)	(558654.2)	(708797.3)
Wins_{t-1}	90967.2	85302.2	61987.1	108444.2	108437.7	93652.0
	(102195.1)	(93046.1)	(102009.4)	(95976.1)	(92164.1)	(96464.9)
Wins_{t-2}	25800.3	40110.4	18517.3	62339.0	58695.5	68866.7
	(70556.3)	(72178.3)	(67634.0)	(66038.7)	(69015.4)	(64484.4)
CoachCareer_{t-1}	68154.7	139515.6	49078.6	-793740.5	-715548.8	-655175.2
	(1985339.3)	(2033843.8)	(2013093.7)	(2029059.8)	(2018001.2)	(2026444.9)
CoachChange	-316877.7	-318515.1	-278585.2	-196192.6	-266078.7	-168104.7
	(380130.5)	(378732.1)	(381359.0)	(382650.4)	(375641.9)	(383067.2)
BowlGame_{t-1}	470586.9	509647.8	546839.3	402070.1	411870.6	450003.5
	(434039.5)	(411079.8)	(443868.3)	(448999.1)	(424706.8)	(434029.7)
BowlWin_{t-1}	-368951.0	-373960.5	-355865.7	-276082.9	-342034.9	-248283.7
	(462170.7)	(448379.6)	(459427.9)	(443369.3)	(442506.3)	(451776.9)
SOS	59731.4	47276.1	75504.1	65062.0	67897.2	61438.7
	(77225.5)	(76807.1)	(76774.9)	(82551.3)	(78234.9)	(80314.4)
TDPts				17143.5	14437.4	21653.0
				(88496.5)	(91088.0)	(88995.5)
TDYds				-737646.8	-564138.7	-660369.2
				(3848779.4)	(3873073.1)	(3894293.5)
TDPassYds				740048.9	565695.0	662956.9
				(3849812.0)	(3873762.0)	(3895411.7)
TDPassTDs				-1090879.0	-981836.9	-1095760.1
				(838052.1)	(842089.9)	(841130.1)
TDRushYds				740323.8	566024.4	663069.9
				(3848707.1)	(3872831.2)	(3894283.6)
TDRushTDs				-417648.9	-400670.5	-455236.2
				(714010.1)	(723405.8)	(719863.4)
HistWins	-16718.8	-10491.5	-20939.5	-11235.2	-17321.1	-4056.9
	(68023.6)	(70742.4)	(69053.1)	(69022.0)	(69583.2)	(70899.3)
HistBowls	-517298.6	-483981.0	-545308.9	-403795.0	-444903.8	-396255.0
	(437519.8)	(440142.0)	(437363.1)	(449847.2)	(448212.7)	(445888.1)

HistBowlWins	114090.4	62807.3	144896.4	-8646.2	75364.9	-26268.0
	(395633.8)	(399301.8)	(386280.8)	(395085.8)	(413892.7)	(398151.1)
Distance	-62052.5**	-62379.8**	-56486.6*	-59148.7*	-60412.0**	-58522.0*
	(31220.9)	(30441.2)	(32607.0)	(29997.7)	(29340.7)	(30238.3)
UndergradPop	-129957.2	-128451.1	-135448.2	-171202.7	-151694.6	-183911.0
	(202802.3)	(212487.1)	(200569.6)	(227020.5)	(219874.1)	(234391.7)
PerCapPI	278907.1	258284.5	242587.2	164184.5	206456.1	169113.4
	(355905.3)	(348088.1)	(347007.7)	(365438.6)	(369615.6)	(360989.3)
GrPerCapPI	7268.9	16402.2	3060.9	39581.2	36382.0	28794.3
	(122013.6)	(123395.1)	(120572.6)	(126992.7)	(127395.7)	(127831.3)
CityPop	2461957.5	-23328931.1	16277245.3	-6244719.4	-22601809.2	-5559699.8
	(47063936.1)	(41714573.9)	(52998112.2)	(42375664.6)	(37904015.9)	(41697652.9)
StatePop	1413565.3	1575566.4	899872.7	739259.9	1571602.0	754123.4
	(3830581.7)	(3770146.1)	(3718579.4)	(3987264.6)	(3829126.2)	(3819461.2)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	832	832	832	832	832	832
Within R^2	0.745	0.744	0.747	0.747	0.747	0.748
Adjusted R^2	0.977	0.977	0.978	0.977	0.977	0.977

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 52

Marginal Revenue Product of Ex-Ante Star College Basketball Players. This table reports fixed effects estimates of an ex-ante star basketball player's marginal revenue product from Model (2.1) over the sample period 2005-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for the ex-ante star measure using the Rivals.com Five Star Rated Recruits are reported.

	(1) 5 Star	
Stars	317810.8*	(172843.9)
Stars_{t-1}	-153329.7	(111547.7)
Stars_{t-2}	275291.1***	(98460.6)
Wins_{t-1}	1000.3	(5259.5)
Wins_{t-2}	8061.1	(5549.4)
$\text{CoachCarTourn}_{t-1}$	72803.8***	(25416.2)
CoachCareer_{t-1}	-60088.0	(370705.7)
CoachChange	-15788.3	(61146.6)
NCAATourn_{t-1}	222111.5**	(96680.5)
Round2_{t-1}	-135047.1	(129603.5)
Sweet16_{t-1}	261181.3	(199306.2)
Elitet8_{t-1}	40738.7	(628306.7)

Final4_{t-1}	204745.1	(497045.2)
Final_{t-1}	207945.0	(324407.0)
Champ_{t-1}	2081114.0**	(813929.5)
NSchlsConf	-36771.4	(40831.8)
NSchlsConfAP	2375.0	(42989.8)
NSchlsConfTourn	-26117.4	(59486.5)
NSchlsConfFF	-61030.1	(84950.2)
SOS	-2996.7	(14171.2)
HistWins	-4910.3	(5227.3)
HistNCAATrn	-27659.0	(74007.5)
HistRound2	-81646.0	(158551.4)
HistSweet16	249765.6	(185963.7)
HistElite8	88674.4	(180113.1)
HistFinal4	-2736.3	(383081.5)
HistFinal	238603.8	(779867.5)
HistChamp	-1951539.0*	(1081441.5)
Distance	-427.9	(1880.0)
UndergradPop	-54183.8	(56809.1)
PerCapPI	12058.9	(38966.3)
GrPerCapPI	13936.7	(16770.2)
CityPop	-1894125.3	(2256818.3)
StatePop	885682.9	(575400.9)
Team Fixed Effects	Yes	
Year Fixed Effects	Yes	
Confr. Fixed Effects	Yes	
N	2256	
Within R^2	0.641	
Adjusted R^2	0.972	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 53

Marginal Revenue Product of Expected and Unexpected Star College Football Players. This table reports fixed effects estimates of the marginal revenue products of expected and unexpected star football players from Model (2.1) over the sample period 2005-2012. Star players are measured according to one of six ex-post performance metrics: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The number of star players on a team are then decomposed into "expected" and "unexpected" star players. Expected stars are those who are stars as measured by ex-post performance who were also top Rivals.com recruits (rated as a 6.1 by Rivals.com). Unexpected stars are those who are stars as measured by ex-post performance who were not rated as a top Rivals.com recruit. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Expected Stars	2720071.0***	3734700.3***	2168631.6	1554102.7	1465080.5	1117334.7
	(922689.4)	(1100931.1)	(1435615.8)	(1100580.6)	(985100.7)	(1021568.3)
Unexpected Stars	1105101.6***	1744591.8	1710230.3***	598792.6**	582975.9**	610990.1**
	(371108.2)	(1114123.8)	(609148.3)	(273821.4)	(259170.2)	(281788.8)
$Stars_{t-1}$	768413.4*	1443313.9*	2117296.5***	463260.7**	481265.2**	631606.8***
	(410486.8)	(793151.1)	(619475.5)	(206689.1)	(197573.7)	(222658.0)
$Stars_{t-2}$	562101.1	-272997.7	122207.5	4177.3	130089.2	155496.2
	(412305.3)	(637024.6)	(500808.9)	(191223.5)	(215417.6)	(228011.4)
$Wins_{t-1}$	-32711.4	3947.3	-65568.7	18878.6	10558.2	2806.8
	(105049.4)	(96470.6)	(101804.2)	(103449.3)	(102256.7)	(101503.3)
$Wins_{t-2}$	41883.4	104381.9*	85021.8	94179.9	77280.7	74368.0
	(56659.1)	(61508.8)	(61971.4)	(65550.6)	(67989.5)	(65025.5)
$CoachCareer_{t-1}$	2590453.4	1959475.8	2491360.8	1370681.5	1347287.4	1466239.9
	(2063239.9)	(2062362.3)	(2079642.2)	(2052005.7)	(2057270.6)	(2071838.5)
CoachChange	-228214.8	-129726.3	-168029.4	-90879.8	-68539.6	-77813.9
	(317638.0)	(305109.5)	(306090.1)	(316197.9)	(316031.3)	(314640.8)
$BowlGame_{t-1}$	859515.7*	702657.6	807492.9*	619397.3	639135.4	625602.6
	(462473.7)	(444804.2)	(455981.4)	(457832.0)	(452720.1)	(451378.9)
$BowlWin_{t-1}$	-382303.9	-234871.3	-185765.7	-384303.1	-397112.6	-391574.2
	(420180.1)	(427313.7)	(403261.7)	(422752.6)	(426789.8)	(427719.2)
SOS	2205.9	13736.9	10276.9	43144.7	44136.7	42736.9
	(53785.8)	(57691.9)	(55583.1)	(56986.1)	(56502.3)	(56737.6)
TDPts		-78795.8	-65124.4	-63258.8	-58334.1	-55882.7
		(76454.5)	(72174.5)	(77500.2)	(77699.1)	(77406.4)
TDYds		1601733.1	1679710.8	1009981.9	1108282.5	1130228.6
		(2954367.3)	(2989466.0)	(3062251.7)	(3058822.4)	(3035647.1)
TDPassYds		-1598204.2	-1676728.1	-1007750.5	-1105647.5	-1128000.7
		(2954865.7)	(2990182.0)	(3063177.9)	(3059702.5)	(3036520.0)
TDPassTDs		-760665.4	-742350.0	-882894.1	-935091.1	-937112.7

		(787011.6)	(771677.1)	(781887.4)	(780463.0)	(774128.3)
TDRushYds		-1596545.1	-1675693.9	-1006269.5	-1104997.3	-1126982.9
		(2954208.7)	(2989375.7)	(3062493.7)	(3059063.0)	(3035847.6)
TDRushTDs		325701.8	266876.2	275879.7	281676.4	295808.3
		(637221.7)	(609615.5)	(655166.9)	(660425.3)	(653769.6)
HistWins	-16545.2	-10323.9	-12596.6	-26207.1	-27405.9	-25882.5
	(46958.4)	(52072.5)	(51087.1)	(50586.9)	(50739.7)	(50567.6)
HistBowls	-525595.8	-580740.3	-502373.1	-498124.0	-498988.4	-511390.4
	(351223.1)	(374918.4)	(365935.8)	(364337.6)	(362668.4)	(360055.0)
HistBowlWins	387046.6	403531.5	345629.4	481730.0	481679.2	458897.2
	(424395.0)	(433124.1)	(434286.9)	(450237.5)	(447948.0)	(442219.8)
Distance	-25887.2	-26121.9	-25630.8	-21458.9	-21585.4	-22095.6
	(16511.1)	(17388.0)	(17055.4)	(17326.9)	(17406.1)	(17307.2)
UndergradPop	-152482.3	-214628.4	-216651.2	-174962.9	-165311.8	-140994.1
	(204249.3)	(203805.9)	(202791.2)	(205692.2)	(202840.5)	(199823.5)
PerCapPI	177110.4	246154.4	270217.5	220570.6	215235.2	207043.5
	(317008.1)	(332009.2)	(321752.5)	(327971.9)	(327810.2)	(322773.5)
GrPerCapPI	31115.0	24619.5	9261.3	5827.7	13506.2	19186.2
	(126520.1)	(128915.1)	(126606.9)	(129516.1)	(128582.5)	(128759.2)
CityPop	16538677.2	-5689565.2	-7176015.7	3746307.5	5152470.8	3054931.6
	(25765585.1)	(29266968.9)	(27632733.9)	(30089762.6)	(30430080.3)	(30159861.3)
StatePop	-158738.0	-274072.4	-215313.1	7725.0	23041.0	89334.8
	(4028068.8)	(4114559.9)	(4197933.3)	(4122496.7)	(4158990.1)	(4108354.4)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.774	0.775	0.779	0.774	0.774	0.774
Adjusted R^2	0.972	0.972	0.972	0.972	0.972	0.972
F-Stat	3.155	1.592	0.0847	0.743	0.799	0.257
P-Value	0.0787	0.210	0.772	0.391	0.373	0.613

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 54

Marginal Revenue Product of Expected and Unexpected Star College Basketball Players. This table reports fixed effects estimates of the marginal revenue products of expected and unexpected star basketball players from Model (2.1) over the sample period 2005-2012. Star players are measured according to one of eight ex-post performance metrics: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. The number of star players on a team are then decomposed into "expected" and "unexpected" star players. Expected stars are those who are stars as measured by ex-post performance who were also a Five Star Rivals.com recruit. Unexpected stars are those who are stars as measured by ex-post performance who were not rated as a Five Star Rivals.com recruit. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expected Stars	1861841.5**	464789.8*	329225.9	180444.1	179831.3	306729.6	351755.1	998639.6***
	(865063.9)	(273430.6)	(249630.0)	(127554.4)	(172113.0)	(186153.0)	(371360.9)	(342904.8)
Unexpected Stars	333899.7	776734.2**	352397.1	216737.3**	714362.0*	495444.7*	305419.4	238009.9*
	(738243.7)	(316859.4)	(255635.8)	(105786.4)	(412900.4)	(298607.7)	(197988.3)	(129040.5)
Stars_{t-1}	134905.6	24465.2	89835.5	-10156.3	203925.4	1087.7	14305.8	29458.2
	(400322.9)	(293195.0)	(179641.7)	(88102.8)	(299590.9)	(231498.6)	(103486.1)	(81657.1)
Stars_{t-2}	207972.0	156328.3	207951.5	224509.8**	248992.5	104352.5	174122.5	84942.4
	(326755.0)	(215013.3)	(157744.2)	(100878.3)	(245767.6)	(201283.0)	(113355.3)	(83915.0)
Wins_{t-1}	5543.7	4694.5	4810.1	6687.5	5017.2	5243.2	5527.5	4591.3
	(4770.4)	(4672.1)	(4707.3)	(4630.3)	(4578.1)	(4611.1)	(4769.1)	(4853.3)
Wins_{t-2}	11622.1***	10809.6**	10366.6**	7456.1	10949.4***	11040.6***	10884.9**	11263.5**
	(4338.1)	(4405.4)	(4409.5)	(4627.5)	(3914.1)	(4097.3)	(4496.4)	(4571.0)
$\text{CoachCarTourn}_{t-1}$	53172.9***	53859.3***	52980.5***	53234.5***	53647.5***	54757.7***	54038.6***	49759.6***
	(16315.8)	(16450.1)	(16460.1)	(16410.5)	(16279.7)	(16333.9)	(16408.0)	(16567.3)
CoachCareer_{t-1}	-108292.0	-37460.2	-58694.4	-96194.1	-91797.4	-90213.0	-78342.4	-81172.7
	(295339.3)	(294202.6)	(296196.7)	(291432.3)	(292420.3)	(293586.7)	(295103.0)	(291725.8)
CoachChange	7141.1	-441.5	5439.5	6026.9	3318.5	1929.6	-2300.2	1314.6
	(61931.0)	(61666.9)	(61114.3)	(61716.1)	(61828.3)	(61519.9)	(61572.5)	(61789.2)
NCAATourn_{t-1}	173884.1**	167026.7**	164312.6**	170068.9**	161540.0**	158358.8**	160024.8**	165053.1**
	(76207.2)	(74672.9)	(75261.0)	(77372.7)	(73351.3)	(74985.9)	(75034.4)	(75412.5)

Round2_{t-1}	-64393.0	-64887.7	-58821.0	-64222.8	-54651.5	-58980.4	-57982.9	-55521.2
	(126197.8)	(125133.2)	(129917.2)	(130414.1)	(128941.6)	(127547.4)	(128295.7)	(126907.9)
Sweet16_{t-1}	269934.2	263658.7	259254.9	308977.5*	270254.8	266852.2	304098.4*	282864.3
	(174618.7)	(183854.5)	(180824.0)	(171083.1)	(182308.7)	(181546.6)	(175207.4)	(172288.3)
Elitet8_{t-1}	-183570.1	-154258.8	-93125.7	-23522.8	-114181.1	-95468.9	-120068.8	-137422.8
	(459748.3)	(460704.4)	(476539.7)	(439939.4)	(468234.2)	(476211.1)	(455800.1)	(453053.4)
Final4_{t-1}	262868.4	345596.7	372028.8	384196.6	338496.2	401319.7	391685.9	390541.6
	(340468.7)	(381278.1)	(370712.4)	(387034.4)	(408233.7)	(413376.0)	(393669.2)	(395324.0)
Final_{t-1}	-49520.9	53317.8	-64363.3	28049.1	-86646.0	-44944.4	-26441.7	-27676.4
	(261964.9)	(336945.4)	(300189.3)	(284678.7)	(326591.1)	(340518.1)	(267465.1)	(262781.9)
Champ_{t-1}	2011876.3**	1848919.8***	1898268.1***	2030169.0***	1756136.6**	1748700.6**	1826897.4***	2001601.0***
	(983545.1)	(546635.7)	(647804.9)	(640066.7)	(773877.7)	(742747.4)	(610354.7)	(650977.6)
NSchlsConf	715.7	1342.4	1273.9	2858.1	3783.8	2417.8	5708.0	-136.0
	(40634.1)	(40315.6)	(40310.1)	(40489.9)	(39983.3)	(40115.1)	(40289.9)	(40457.8)
NSchlsConfAP	-39922.9	-43521.1	-46133.2	-38250.9	-38967.9	-41762.8	-42048.4	-41731.0
	(38762.4)	(41250.5)	(40962.9)	(40905.1)	(41741.5)	(42169.4)	(41064.8)	(40204.5)
NSchlsConfTourn	2638.4	6490.1	4997.1	520.0	8494.3	7314.8	6282.6	4506.9
	(39649.6)	(38937.3)	(38745.2)	(39111.6)	(38799.4)	(38833.9)	(39544.7)	(39318.3)
NSchlsConfFF	-96038.3	-95249.2	-84515.5	-87378.8	-99437.2	-96075.8	-87009.4	-86949.2
	(81320.3)	(80445.3)	(81295.5)	(84186.5)	(81884.6)	(81127.4)	(81277.0)	(80790.5)
SOS	3653.7	2017.5	2270.3	1310.9	1762.3	1512.0	1374.0	1013.3
	(12285.8)	(12168.6)	(12315.9)	(12175.9)	(12195.2)	(12127.6)	(12252.9)	(12199.5)
HistWins	-3275.3	-3606.0	-3702.0	-3820.5	-3797.1	-3596.3	-3394.6	-3289.9
	(2988.2)	(2985.3)	(2990.0)	(2980.8)	(3007.9)	(3032.3)	(2973.8)	(2963.1)
HistNCAATrn	-22581.9	-21408.3	-20511.1	-38384.8	-29280.6	-25905.1	-27405.0	-31626.3
	(59513.1)	(60650.2)	(60475.8)	(59013.6)	(59886.1)	(59691.1)	(60373.6)	(59712.2)
HistRound2	-73686.3	-47186.6	-46813.1	-58698.4	-62770.5	-69370.4	-62061.1	-65518.0
	(111950.8)	(112900.5)	(112751.6)	(113242.3)	(112907.6)	(113545.8)	(112763.7)	(112931.8)
HistSweet16	-94271.4	-112834.9	-91054.2	-57515.5	-78928.9	-76390.2	-95879.0	-104352.8
	(144639.0)	(146956.7)	(141947.9)	(138001.4)	(141253.1)	(144594.2)	(150578.5)	(149206.9)
HistElite8	151893.0	132758.8	152479.2	160620.1	125282.4	126904.8	99417.2	102743.8
	(192402.0)	(195962.9)	(195915.5)	(189163.5)	(190183.8)	(191309.5)	(196454.9)	(197994.3)
HistFinal4	243743.3	373651.6	406694.9	415969.1	344176.5	309269.4	319211.5	252523.1
	(300480.6)	(317226.6)	(323887.9)	(332454.9)	(321350.1)	(324644.4)	(323956.9)	(323615.6)
HistFinal	46621.3	249335.6	221522.8	151931.6	260305.0	227185.3	164304.2	149642.0

	(600326.1)	(596545.3)	(596074.5)	(574160.5)	(565424.3)	(573067.2)	(588679.7)	(596535.0)
HistChamp	-732156.3	-838407.1	-795661.5	-748260.4	-768595.0	-802130.4	-791374.5	-795041.8
	(816413.4)	(810434.0)	(808279.5)	(782478.9)	(785216.7)	(814934.1)	(803125.9)	(789442.9)
Distance	-1028.5	-969.5	-1074.7	-1296.0	-1257.8	-1186.8	-1387.3	-1145.0
	(1511.8)	(1557.6)	(1543.0)	(1572.4)	(1588.1)	(1552.1)	(1547.5)	(1529.8)
UndergradPop	-50406.9	-47128.0	-49909.3	-46795.7	-49340.5	-47731.9	-44455.8	-51790.0
	(39091.6)	(38514.6)	(38966.0)	(39404.1)	(38666.3)	(39170.2)	(38746.4)	(37071.7)
PerCapPI	14919.1	10811.5	9450.8	2647.3	15184.9	14988.6	9968.5	9645.4
	(41201.9)	(40806.3)	(39813.0)	(39926.3)	(40578.8)	(40492.9)	(40076.8)	(40661.7)
GrPerCapPI	5392.7	9524.1	10728.7	11610.9	9186.8	10785.9	8613.6	9186.7
	(15781.7)	(15596.3)	(15528.0)	(15876.3)	(15655.1)	(15886.4)	(15677.8)	(15875.9)
CityPop	833048.0	916194.4	918594.8	889769.3	1080767.6	1098545.0	812712.7	900306.0
	(1887909.2)	(1862919.2)	(1871686.3)	(1894949.3)	(1848625.0)	(1834969.5)	(1862170.1)	(1893539.6)
StatePop	3224.6	57476.8	33880.0	73960.6	87689.1	87860.3	71387.8	53784.5
	(425925.1)	(409078.4)	(417295.5)	(431915.5)	(422900.1)	(422559.0)	(417247.8)	(422258.5)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820	2820	2820	2820	2820
Within R^2	0.671	0.670	0.668	0.672	0.668	0.669	0.668	0.670
Adjusted R^2	0.969	0.968	0.968	0.969	0.968	0.968	0.968	0.968
F-Stat	1.560	0.431	0.00326	0.0594	1.476	0.369	0.0122	5.967
P-Value	0.213	0.512	0.954	0.808	0.225	0.544	0.912	0.0152

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 55

First Stage Regression of the Number of Star Football Players on the Number of Injured Star Players in the Previous Season. This table reports the first stage of the instrumental variable estimates in Table 56. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Injured Stars$_{t-1}$	3.792***	0.513	2.467***	2.845***	2.618***	1.436
	(0.986)	(0.982)	(0.875)	(0.925)	(0.966)	(0.889)
Stars$_{t-1}$	-0.170***	-0.109***	-0.130***	-0.123***	-0.148***	-0.195***
	(0.0363)	(0.0360)	(0.0360)	(0.0373)	(0.0373)	(0.0370)
Stars$_{t-2}$	-0.196***	-0.207***	-0.230***	-0.202***	-0.200***	-0.222***
	(0.0354)	(0.0343)	(0.0353)	(0.0370)	(0.0372)	(0.0368)
Wins$_{t-1}$	0.0258**	0.00647	0.0101	0.0291*	0.0289	0.0287*
	(0.0123)	(0.00558)	(0.00723)	(0.0169)	(0.0178)	(0.0163)
Wins$_{t-2}$	-0.00888	-0.00140	0.000586	0.00298	0.00531	0.00813
	(0.00821)	(0.00377)	(0.00491)	(0.0123)	(0.0129)	(0.0116)
CoachCareer$_{t-1}$	-0.259	-0.0940	-0.157	0.306	0.351	0.162
	(0.210)	(0.0966)	(0.124)	(0.297)	(0.310)	(0.283)
CoachChange	-0.0552	-0.000168	-0.0174	-0.126**	-0.150**	-0.126**
	(0.0393)	(0.0181)	(0.0231)	(0.0560)	(0.0584)	(0.0534)
BowlGame$_{t-1}$	-0.0407	0.00615	0.0140	-0.0720	-0.0553	-0.0212
	(0.0570)	(0.0260)	(0.0333)	(0.0806)	(0.0839)	(0.0766)
BowlWin$_{t-1}$	-0.0211	-0.0125	-0.0320	0.0225	0.0463	0.0539
	(0.0440)	(0.0204)	(0.0258)	(0.0621)	(0.0648)	(0.0593)
SOS	0.00126	0.00921**	0.0108**	-0.00576	-0.00307	-0.00195
	(0.00798)	(0.00375)	(0.00478)	(0.0116)	(0.0121)	(0.0111)
TDPts		-0.00623	-0.0180***	-0.0491***	-0.0647***	-0.0638***
		(0.00527)	(0.00669)	(0.0163)	(0.0170)	(0.0155)
TDYds		-0.373**	-0.467**	-0.339	-0.510	-0.189
		(0.151)	(0.192)	(0.466)	(0.487)	(0.445)
TDPassYds		0.373**	0.468**	0.343	0.513	0.192
		(0.151)	(0.192)	(0.466)	(0.487)	(0.445)
TDPassTDs		0.0217	0.0376	0.304**	0.437***	0.392***
		(0.0400)	(0.0509)	(0.124)	(0.129)	(0.118)
TDRushYds		0.373**	0.467**	0.341	0.512	0.192
		(0.151)	(0.192)	(0.466)	(0.487)	(0.445)
TDRushTDs		0.0134	0.0772	0.169	0.239*	0.224*
		(0.0406)	(0.0516)	(0.125)	(0.131)	(0.120)
HistWins	-0.0103	-0.00523*	-0.00754**	-0.00335	-0.00353	-0.00542
	(0.00649)	(0.00299)	(0.00380)	(0.00924)	(0.00964)	(0.00880)

HistBowls	-0.00220	0.0171	0.0110	0.0160	0.0225	0.0519
	(0.0400)	(0.0184)	(0.0234)	(0.0566)	(0.0591)	(0.0540)
HistBowlWins	-0.0172	-0.0224	0.00111	-0.151***	-0.145***	-0.117**
	(0.0362)	(0.0166)	(0.0212)	(0.0515)	(0.0538)	(0.0490)
Distance	-0.000793	0.000485	0.000201	-0.00163	-0.00112	-0.000597
	(0.00180)	(0.000828)	(0.00106)	(0.00257)	(0.00268)	(0.00245)
UndergradPop	-0.0363	-0.00142	-0.00306	-0.0345	-0.0366	-0.0545*
	(0.0230)	(0.0105)	(0.0134)	(0.0326)	(0.0341)	(0.0312)
PerCapPI	0.00806	-0.0191	-0.0236	-0.0146	-0.00635	-0.00232
	(0.0296)	(0.0137)	(0.0175)	(0.0424)	(0.0442)	(0.0404)
GrPerCapPI	-0.00287	0.00656	0.00842	0.0204	0.0144	0.00554
	(0.0116)	(0.00538)	(0.00685)	(0.0166)	(0.0173)	(0.0158)
CityPop	1.498	4.596***	5.176**	1.236	0.560	3.020
	(3.551)	(1.626)	(2.075)	(5.019)	(5.239)	(4.782)
StatePop	-0.249	0.147	0.228	0.504	0.476	0.430
	(0.329)	(0.153)	(0.195)	(0.471)	(0.492)	(0.449)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.263	0.232	0.280	0.312	0.311	0.304
F-Stat	14.81	0.273	7.944	9.458	7.346	2.607
p-value	0.000129	0.602	0.00494	0.00217	0.00687	0.107

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 56

Marginal Revenue Product of Star College Football Players. This table reports instrumental variable estimates of a star football player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. The F-statistics and corresponding p-values from the first stage regression are reported at the bottom of the table.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
Stars	3352048.8*	31016231.2	4461936.1	-325897.0	-451761.8	-638610.6
	(2029944.2)	(63869507.7)	(4631794.7)	(1761384.2)	(1925194.5)	(3548987.3)
Stars_{t-1}	1145799.4**	4683159.5	2482640.5***	336907.6	315453.9	374615.7
	(449170.6)	(7042909.1)	(774044.5)	(307185.4)	(356973.7)	(740135.0)
Stars_{t-2}	939580.0**	5721367.3	719271.2	-182067.4	-72906.5	-115251.2

	(466323.3)	(13159114.6)	(1104045.3)	(392099.1)	(414365.1)	(786394.5)
Wins_{t-1}	-84306.6	-178687.0	-89140.2	47064.3	43107.9	40095.6
	(107624.2)	(440717.8)	(102550.1)	(106177.7)	(109552.0)	(139836.1)
Wins_{t-2}	65369.0	143180.8	82589.2	100274.1	85756.2	85903.6
	(66246.3)	(154561.8)	(64187.3)	(67170.6)	(68894.9)	(74135.2)
CoachCareer_{t-1}	3085225.6*	4644883.5	2880010.4	1544703.0	1627646.1	1628212.6
	(1709751.7)	(6796621.5)	(1757220.8)	(1694773.6)	(1751238.6)	(1720642.1)
CoachChange	-92800.2	-134222.5	-114945.5	-205497.6	-226326.7	-235655.8
	(330065.1)	(603436.0)	(314978.0)	(369170.3)	(412573.9)	(533989.0)
BowlGame_{t-1}	941503.6**	505151.5	769309.4*	554650.7	578689.7	602101.5
	(451919.7)	(962634.1)	(438882.7)	(448386.7)	(445757.8)	(441982.9)
BowlWin_{t-1}	-339821.8	116548.9	-107854.0	-366926.5	-352897.6	-328632.0
	(344562.8)	(1019531.5)	(362519.6)	(336782.8)	(345584.6)	(382430.0)
SOS	2808.4	-251188.5	-17497.1	36891.5	40216.5	40041.3
	(62313.5)	(600709.3)	(79332.7)	(64082.0)	(63776.4)	(64081.8)
TDPts		95283.4	-16914.4	-103381.2	-121634.2	-134189.5
		(422573.0)	(119356.1)	(121864.3)	(150995.6)	(241448.5)
TDYds		12124605.3	2783724.8	732582.7	589777.6	916281.0
		(24000468.9)	(3165958.8)	(2548832.4)	(2649268.3)	(2587671.8)
TDPassYds		-12134939.9	-2784401.9	-727063.8	-583979.0	-910093.9
		(24030000.1)	(3169718.9)	(2549810.5)	(2650994.6)	(2589766.5)
TDPassTDs		-1337491.2	-835120.9	-639208.3	-513437.1	-459697.3
		(1854185.0)	(682423.5)	(843389.6)	(1059830.2)	(1529477.3)
TDRushYds		-12121168.6	-2781272.4	-726947.2	-583839.7	-910006.1
		(24004226.4)	(3168012.2)	(2550054.2)	(2651352.9)	(2589907.8)
TDRushTDs		-7320.5	72452.6	383251.2	483927.6	554289.3
		(1535094.0)	(746527.1)	(728374.6)	(804437.9)	(1027878.3)
HistWins	-204.9	136354.3	6045.6	-30329.2	-32342.2	-33341.9
	(54792.1)	(350503.6)	(60459.9)	(50183.9)	(50555.4)	(53359.4)
HistBowls	-480759.0	-1027815.2	-530246.5*	-458221.4	-448684.9	-429201.8
	(312590.2)	(1262074.9)	(312218.4)	(309453.7)	(313479.2)	(367237.6)
HistBowlWins	422329.2	1046815.1	353565.4	321786.8	311813.6	300306.4
	(282442.1)	(1538861.8)	(276004.7)	(398068.3)	(408742.9)	(516667.7)
Distance	-22733.9	-40357.4	-25887.6*	-23063.5	-22641.2	-22712.3
	(14176.4)	(41881.0)	(13796.1)	(14421.4)	(14316.8)	(14327.6)
UndergradPop	-59394.4	-157068.6	-205559.1	-209251.8	-202254.1	-209097.8
	(194915.1)	(362905.3)	(175858.0)	(187389.2)	(191935.6)	(264231.7)
PerCapPI	169103.1	821280.9	339000.2	195442.0	196669.3	195767.3
	(231400.6)	(1327571.9)	(255842.7)	(232845.0)	(232035.0)	(232387.3)
GrPerCapPI	25720.7	-175530.1	-16468.8	26424.2	28226.6	25687.8
	(91006.8)	(460864.0)	(98700.0)	(97968.4)	(95411.5)	(93421.9)
CityPop	10240343.5	-140315603.5	-21170577.7	5516002.0	6535518.0	6590143.6
	(27824837.4)	(298784720.9)	(36166628.4)	(27302002.9)	(27369371.1)	(29579455.6)
StatePop	548420.4	-4408405.5	-799029.5	541864.3	579277.8	666830.0
	(2620870.0)	(10743151.1)	(2761825.7)	(2681236.6)	(2703656.7)	(2963498.3)
Team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040	1040	1040
Within R^2	0.755	0.0766	0.769	0.766	0.764	0.762

FS F-Stat	14.81	0.273	7.944	9.458	7.346	2.607
FS p-value	0.000129	0.602	0.00494	0.00217	0.00687	0.107

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 57

First Stage Regression of the Number of Star Basketball Players on the Number of Injured Star Players in the Previous Season. This table reports the first stage of the instrumental variable estimates in Table 58. Standard errors are in parentheses and have been clustered by team. Estimates for two different measures of star player are reported: (1) Top 10 Points Scorers and (2) Top 20 Points Scorers.

	(1) PTS 10		(2) PTS 20	
Injured Stars$_{t-1}$			2.586	(2.762)
Stars$_{t-1}$	-0.0931***	(0.0212)	-0.158***	(0.0216)
Stars$_{t-2}$	-0.209***	(0.0213)	-0.238***	(0.0215)
Wins$_{t-1}$	0.000296	(0.00101)	0.00275*	(0.00141)
Wins$_{t-2}$	0.00215**	(0.000856)	0.00405***	(0.00120)
CoachCarTourn$_{t-1}$	-0.000271	(0.00213)	0.00430	(0.00295)
CoachCareer$_{t-1}$	-0.0371	(0.0669)	-0.0602	(0.0929)
CoachChange	0.00326	(0.00922)	0.00307	(0.0128)
NCAATourn$_{t-1}$	0.0158	(0.0141)	0.0194	(0.0196)
Round2$_{t-1}$	0.00118	(0.0172)	-0.00363	(0.0239)
Sweet16$_{t-1}$	-0.0174	(0.0225)	0.0411	(0.0313)
Elitet8$_{t-1}$	0.0562*	(0.0334)	0.0928**	(0.0465)
Final4$_{t-1}$	0.0644	(0.0451)	0.0606	(0.0628)
Final$_{t-1}$	-0.0412	(0.0625)	-0.0502	(0.0871)
Champ$_{t-1}$	-0.0660	(0.0623)	-0.200**	(0.0871)
NSchlsConf	-0.00756	(0.00580)	-0.00471	(0.00806)
NSchlsConfAP	-0.00300	(0.00612)	-0.0121	(0.00850)
NSchlsConfTourn	0.00499	(0.00491)	0.00610	(0.00682)
NSchlsConfFF	0.00221	(0.0100)	0.00525	(0.0139)
SOS	0.00281	(0.00255)	0.00556	(0.00354)
HistWins	-0.000111	(0.000563)	-0.000373	(0.000782)
HistNCAATrn	0.000888	(0.00966)	0.0248*	(0.0134)
HistRound2	-0.00983	(0.0126)	0.00563	(0.0175)
HistSweet16	0.0230	(0.0167)	0.0304	(0.0232)
HistElite8	0.0375	(0.0242)	0.0122	(0.0336)
HistFinal4	-0.0195	(0.0308)	0.0560	(0.0428)
HistFinal	-0.0465	(0.0444)	-0.0810	(0.0617)
HistChamp	-0.120***	(0.0452)	0.0107	(0.0627)

Distance	0.000136	(0.000342)	-0.000139	(0.000474)
UndergradPop	-0.00969	(0.00596)	-0.00982	(0.00829)
PerCapPI	0.00178	(0.00680)	0.00465	(0.00945)
GrPerCapPI	0.000635	(0.00289)	-0.00178	(0.00401)
CityPop	0.0606	(0.313)	0.141	(0.435)
StatePop	0.0760	(0.0683)	0.0456	(0.0948)
Team Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Confr. Fixed Effects	Yes		Yes	
N	2820		2820	
Within R^2	0.199		0.222	
F-Stat	.		0.876	
p-value	.		0.349	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 58

Marginal Revenue Product of Star College Basketball Players. This table reports instrumental variable estimates of a star basketball player's marginal revenue product from Model (2.1) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for two different measures of star player are reported: (1) Top 10 Points Scorers and (2) Top 20 Points Scorers. The F-statistics and corresponding p-values from the first stage regression are reported at the bottom of the table.

	(1) PTS 10		(2) PTS 20	
Stars			-2060650.7	(4712952.1)
Stars_{t-1}	-14324.8	(109625.6)	-341069.3	(742329.6)
Stars_{t-2}	109321.6	(110055.9)	-482453.9	(1119310.9)
Wins_{t-1}	5621.2	(5236.7)	11295.1	(14340.6)
Wins_{t-2}	11545.7***	(4428.7)	20542.6	(19901.9)
$\text{CoachCarTourn}_{t-1}$	54048.2***	(11019.9)	62527.3***	(24077.2)
CoachCareer_{t-1}	-89894.0	(346243.7)	-215499.8	(498255.9)
CoachChange	-1326.2	(47678.2)	5237.9	(57968.6)
NCAATourn_{t-1}	164567.1**	(73133.0)	205250.6	(125761.7)
Round2_{t-1}	-57319.5	(88987.7)	-64365.0	(106811.9)
Sweet16_{t-1}	297907.1**	(116506.6)	384564.2	(237000.8)
Elitet8_{t-1}	-101380.5	(172997.3)	95150.5	(481962.8)
Final4_{t-1}	411656.3*	(233528.9)	535165.9	(397265.9)
Final_{t-1}	-39245.0	(323023.4)	-138343.0	(452842.0)
Champ_{t-1}	1802254.2***	(322007.8)	1391137.2	(1020610.9)
NSchlsConf	3510.1	(30022.5)	-6613.3	(41622.8)

NSchlsConfAP	-43115.1	(31677.8)	-68294.1	(68451.3)
NSchlsConfTourn	7994.4	(25413.8)	21652.5	(41610.2)
NSchlsConfFF	-86345.9*	(51939.1)	-74744.8	(66352.6)
SOS	2231.1	(13166.1)	13503.0	(30288.3)
HistWins	-3437.9	(2912.1)	-4224.9	(3915.4)
HistNCAATrn	-26991.9	(49974.5)	24703.1	(131056.4)
HistRound2	-65125.8	(65300.6)	-52673.9	(82022.6)
HistSweet16	-88887.3	(86527.4)	-27972.7	(177136.3)
HistElite8	110520.5	(125260.0)	133288.4	(160069.4)
HistFinal4	313416.4**	(159279.9)	424863.5	(326582.1)
HistFinal	150795.5	(229661.3)	-13264.2	(466980.9)
HistChamp	-830267.5***	(233714.0)	-808790.9***	(281542.2)
Distance	-1348.6	(1768.0)	-1580.6	(2201.1)
UndergradPop	-47495.4	(30836.0)	-68863.8	(58763.4)
PerCapPI	10535.1	(35178.4)	21206.2	(47344.4)
GrPerCapPI	8847.5	(14948.2)	5920.1	(19544.1)
CityPop	832254.9	(1620582.9)	1119659.8	(2026988.6)
StatePop	95094.5	(353365.5)	198732.0	(470018.7)
Team Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Confr. Fixed Effects	Yes		Yes	
N	2820		2820	
Within R^2	0.667		0.533	
FS F-Stat	.		0.876	
FS p-value	.		0.349	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 59

Marginal Revenue Product of Gaining Versus Losing a Star College Football Player. This table reports first-difference estimates of the marginal revenue product assocaited with gaining or losing a star football player from Model (2.6) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone. F-statistics and corresponding p-values for the null hypothesis that gaining a star and losing a star are statistically equivalent are reported at the bottom of the table.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds	(5) PERTDsYds	(6) PER
$\Delta\text{Stars}_t \times$GainStars	767259.7*	2591514.5**	1541978.3*	764154.7**	732774.2**	751373.8**
	(409898.9)	(1012532.7)	(822193.9)	(340852.0)	(318469.5)	(349115.1)
$\lvert\Delta\text{Stars}_t\rvert \times$LoseStars	-971939.3*	343956.3	-1333385.4*	-814791.5***	-771677.6***	-747472.0***
	(501617.8)	(1150132.4)	(802480.9)	(265015.4)	(252527.0)	(281734.2)
ΔStars_{t-1}	612304.6*	887716.4	2065735.2***	580330.8***	586439.8***	722016.3***
	(346843.1)	(900151.3)	(757039.8)	(205986.1)	(208918.3)	(217054.1)
ΔStars_{t-2}	213627.3	-364581.0	213379.7	-40878.9	90550.3	227177.4
	(354136.4)	(755705.8)	(548891.4)	(172334.5)	(189095.0)	(207782.0)
ΔWins_{t-1}	-50677.6	-43497.2	-91160.7	-29362.4	-35728.6	-42665.2
	(77187.3)	(73615.2)	(84659.0)	(82896.8)	(83423.3)	(83930.2)
ΔWins_{t-2}	21278.1	29304.0	22302.5	41061.2	23842.6	9814.5
	(57648.9)	(54673.9)	(55369.7)	(61214.9)	(64296.4)	(62399.9)
$\Delta\text{CoachCareer}_{t-1}$	912558.7	454746.2	876351.3	-122683.0	-152453.2	-47862.7
	(1286349.9)	(1244946.3)	(1279144.8)	(1317458.3)	(1316553.7)	(1319062.2)
ΔCoachChange	-97085.9	-20920.0	-52804.1	-3982.4	8676.0	5092.7
	(250904.1)	(251909.8)	(241798.2)	(248061.4)	(248196.3)	(246851.6)
$\Delta\text{BowlGame}_{t-1}$	424009.9	379995.9	425971.7	372331.5	384951.3	367084.9
	(357984.3)	(348605.9)	(358855.9)	(356627.4)	(357303.5)	(357193.9)
$\Delta\text{BowlWin}_{t-1}$	-217844.4	-81500.2	-48854.6	-225603.7	-243262.9	-244554.3
	(352866.9)	(340343.9)	(327967.9)	(342580.7)	(346082.7)	(347783.0)
ΔSOS_t	25226.9	36307.1	36386.7	51763.8	51629.4	49329.6
	(48376.9)	(52666.6)	(52568.4)	(49806.2)	(49935.8)	(50717.7)
ΔTDPts_t		7601.7	2953.0	37239.0	40078.3	38347.0
		(68879.7)	(69007.9)	(71909.8)	(72314.3)	(71997.4)
ΔTDYds_t		1559251.2	1500897.1	1158677.4	1224378.9	1239798.8
		(2068758.5)	(2097760.7)	(2102810.0)	(2115404.3)	(2129462.3)
$\Delta\text{TDPassYds}_t$		-1558340.9	-1498897.8	-1158655.2	-1224202.8	-1239681.9
		(2068368.6)	(2097498.8)	(2102910.7)	(2115458.5)	(2129562.8)
$\Delta\text{TDPassTDs}_t$		-934702.4	-874256.5	-1129918.6*	-1156894.6*	-1136985.5*
		(623161.2)	(612242.4)	(636568.1)	(642907.3)	(634898.1)
$\Delta\text{TDRushYds}_t$		-1552520.9	-1493471.6	-1152702.2	-1218503.7	-1233715.0
		(2067733.5)	(2096871.4)	(2102205.6)	(2114792.7)	(2128867.4)
$\Delta\text{TDRushTDs}_t$		-370275.5	-355365.1	-536451.4	-525915.9	-497106.9
		(501973.3)	(488963.1)	(509249.8)	(509500.7)	(501959.0)
$\Delta\text{HistWins}_t$	2185.7	944.9	7966.4	-3497.8	-916.2	-421.8
	(53352.1)	(57340.9)	(57150.2)	(56075.4)	(56298.1)	(56233.8)
$\Delta\text{HistBowls}_t$	-426902.0	-472651.5	-456521.2	-426150.3	-434185.5	-464150.7
	(322349.8)	(333650.0)	(323375.6)	(320136.2)	(321525.5)	(324118.2)
$\Delta\text{HistBowlWins}_t$	339511.3	379703.9	348653.6	464824.7	446929.8	458321.2
	(380937.8)	(358864.7)	(355292.0)	(359584.5)	(358118.4)	(356427.6)
$\Delta\text{Distance}_t$	-28744.0*	-26242.5	-32002.6**	-26050.0*	-25089.5	-24823.9
	(15314.8)	(16055.5)	(15693.9)	(15472.6)	(15520.4)	(15606.8)
$\Delta\text{UndergradPop}_t$	-315703.1*	-347044.6*	-348604.4*	-312620.9*	-310304.3*	-304849.5*
	(175956.8)	(185787.1)	(186828.5)	(168214.9)	(169465.8)	(170093.7)
$\Delta\text{PerCapPI}_t$	203744.0	208831.6	255825.8	239254.2	238047.8	221228.8
	(291264.7)	(305451.8)	(297124.9)	(303221.7)	(303020.1)	(297156.6)
$\Delta\text{GrPerCapPI}_t$	-7641.1	11150.3	1484.3	-11145.8	-6783.0	3410.9
	(105097.0)	(104790.2)	(104050.2)	(109388.5)	(108585.8)	(106166.4)

ΔCityPop$_t$	26402100.7	23576891.4	15161309.6	18179455.9	18569451.6	16778202.8
	(23311337.4)	(25722588.5)	(22852332.3)	(24443375.9)	(23810869.3)	(23500378.3)
ΔStatePop$_t$	-1139331.8	-831547.0	-840449.8	-1045157.7	-1032282.4	-779417.3
	(2790221.1)	(2851582.6)	(2822177.6)	(2761412.6)	(2820483.5)	(2805165.1)
ΔConference	203195.8	177432.1	147283.0	222451.9	218244.9	208360.7
	(225037.5)	(219374.1)	(223933.8)	(224730.7)	(231127.3)	(233022.0)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	936	936	936	936	936	936
R^2	0.145	0.160	0.169	0.168	0.166	0.162
F-Stat	0.0884	4.703	0.0252	0.0142	0.00972	0.0000817
P-Value	0.767	0.0324	0.874	0.905	0.922	0.993

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 60

Marginal Revenue Product of Gaining Versus Losing a Star College Basketball Player. This table reports first-difference estimates of the marginal revenue product associated with gaining or losing a star basketball player from Model (2.6) over the sample period 2003-2012. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, (4) NBA Drafted Players, (5) NBA Top 5 Draft Pick, (6) NBA Top 10 Draft Pick, (7) Top 10 Points Scorers, and (8) Top 20 Points Scorers. F-statistics and corresponding p-values for the null hypothesis that gaining a star and losing a star are statistically equivalent are reported at the bottom of the table.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\text{Stars}_t \times \text{GainStars}$	1249401.5**	1022006.2***	385237.4	262206.6**	612977.8**	542524.9**	438588.8	454806.1**
	(567449.1)	(251755.9)	(255794.4)	(114139.3)	(259816.6)	(222327.7)	(273236.2)	(213839.4)
$\lvert\Delta\text{Stars}_t\rvert \times \text{LoseStars}$	-1069510.3*	18293.2	-178812.8	-7130.9	-42078.2	-80122.6	-239836.4	-283733.6*
	(609260.0)	(406132.0)	(226092.5)	(130412.1)	(527181.9)	(242545.4)	(190480.7)	(160232.2)
ΔStars_{t-1}	1207782.7***	-21121.5	80006.9	-35134.1	22517.7	59302.2	68989.6	123678.1
	(440837.3)	(216268.1)	(129649.5)	(105900.3)	(397336.2)	(191673.0)	(119312.7)	(109812.7)
ΔStars_{t-2}	556357.4	79487.6	3385.2	150899.9	-30961.0	-61833.0	79607.9	73114.6
	(373802.4)	(213477.4)	(156103.7)	(108005.0)	(250395.0)	(201046.3)	(111521.2)	(91096.6)
ΔWins_{t-1}	-1247.9	-1627.2	-925.6	1387.3	-570.7	-870.8	-387.1	-1093.8
	(4714.6)	(4596.3)	(4713.5)	(4595.5)	(4713.6)	(4777.7)	(4709.6)	(4727.7)
ΔWins_{t-2}	6196.2	5979.2	7156.4	4459.1	7047.2	7190.0	6641.6	5928.1
	(5072.0)	(5003.6)	(5111.0)	(5392.1)	(5214.1)	(5277.7)	(5244.8)	(5091.1)
$\Delta\text{CoachCarTourn}_{t-1}$	33322.0*	32429.0*	33551.3*	34339.5*	33184.8*	33185.7*	33460.9*	32869.6*
	(18719.3)	(18740.7)	(18768.4)	(18589.9)	(18539.4)	(18330.8)	(18767.7)	(18733.4)
$\Delta\text{CoachCareer}_{t-1}$	261375.0	306004.8	270328.0	173724.8	228596.8	245944.5	271100.2	270579.4
	(260165.1)	(259158.7)	(263841.6)	(257149.4)	(259998.5)	(261600.1)	(255880.3)	(255592.1)
$\Delta\text{CoachChange}_t$	-4662.0	-5621.6	-3551.2	-4648.5	-4245.9	-5000.7	-8226.6	-8423.6
	(54892.4)	(54904.7)	(54898.3)	(54791.6)	(54830.2)	(54502.3)	(54825.1)	(55038.8)
$\Delta\text{NCAATourn}_{t-1}$	74306.0	75031.6	64787.6	73656.1	64953.1	61950.2	69087.9	63015.1
	(68325.6)	(67682.6)	(67249.6)	(67680.5)	(68292.0)	(69341.9)	(68127.8)	(68072.0)
$\Delta\text{Round2}_{t-1}$	-85566.5	-87958.0	-78463.5	-78593.4	-79557.4	-80160.0	-74907.3	-76394.1
	(103404.2)	(102920.8)	(104784.9)	(107142.6)	(104542.7)	(105230.9)	(103345.5)	(102453.6)

ΔSweet16$_{t-1}$	94961.9	129503.1	119467.6	163591.8	119382.4	117748.4	162388.7	140004.0
	(118727.7)	(125350.5)	(127108.9)	(122943.3)	(128062.4)	(126737.5)	(124593.4)	(123426.1)
ΔElite8$_{t-1}$	-313415.6	-300767.6	-260119.8	-177421.6	-285888.7	-314854.4	-300653.1	-302507.1
	(338725.2)	(335751.8)	(342806.3)	(321332.5)	(341478.4)	(344208.1)	(335867.0)	(334730.9)
ΔFinal4$_{t-1}$	-212224.6	-146280.5	-190996.4	-195684.9	-230527.4	-218177.9	-163739.8	-161077.6
	(405958.8)	(412048.7)	(387459.7)	(404429.2)	(423498.6)	(418915.5)	(404755.2)	(406860.1)
ΔFinal$_{t-1}$	-18821.5	28868.6	-24866.4	175601.5	50331.6	23258.8	8452.3	25085.8
	(257894.2)	(364194.3)	(315975.9)	(221087.0)	(237051.3)	(261103.2)	(264954.9)	(270258.4)
ΔWinner$_{t-1}$	509139.3	1142686.0***	1010633.3**	1253753.5***	893806.3*	806893.7*	1047106.2**	1066573.2**
	(488615.4)	(378916.4)	(441369.9)	(360178.5)	(461283.2)	(476800.0)	(422135.8)	(424646.5)
ΔNSchlsConf$_t$	43565.7	39086.8	38999.6	45340.3	40658.4	37977.5	46164.2	43453.0
	(46534.4)	(46219.4)	(46685.8)	(46526.9)	(45925.2)	(46274.6)	(46400.9)	(45489.1)
ΔNSchlsConfAP$_t$	-13223.1	-15063.1	-18015.9	-8326.7	-13161.5	-12519.7	-14444.4	-12056.0
	(47198.3)	(48696.7)	(48558.0)	(49813.4)	(49081.6)	(49199.4)	(47567.6)	(46331.6)
ΔNSchlsConfTourn$_t$	-12230.0	-13728.5	-9542.5	-15756.4	-7652.7	-8219.7	-12117.1	-10485.2
	(45353.9)	(45363.6)	(45443.1)	(44860.6)	(45163.6)	(44970.9)	(45709.2)	(45368.3)
ΔNSchlsConfFF$_t$	-56618.2	-52555.6	-56434.4	-64438.6	-59816.9	-59716.8	-58105.2	-59302.0
	(63733.8)	(61708.4)	(63367.8)	(64900.9)	(61963.4)	(61385.9)	(61695.8)	(61930.0)
ΔSOS$_{t-1}$	13231.3	12325.2	12846.7	11254.5	11819.7	11835.3	12145.7	11264.5
	(9953.0)	(9970.2)	(10090.9)	(9944.5)	(9939.0)	(10084.5)	(9976.2)	(9956.1)
ΔHistWins$_t$	-6222.3**	-5818.7*	-6305.5**	-6493.2**	-6247.7**	-6407.3**	-6502.9**	-6082.2**
	(3094.4)	(3082.1)	(3117.0)	(3095.3)	(3147.7)	(3166.9)	(3083.4)	(3041.5)
ΔHistNCAATrn$_t$	14013.2	5408.3	17941.3	10563.6	15451.9	18739.7	19069.8	15001.7
	(65225.8)	(65488.5)	(64698.8)	(66931.3)	(65450.8)	(65126.7)	(65956.8)	(65770.3)
ΔHistRnd2$_t$	-34142.4	-27453.0	-17689.8	-26478.9	-25598.4	-22550.1	-13689.2	-21391.6
	(130393.8)	(129651.7)	(131531.5)	(127870.7)	(131487.3)	(131762.4)	(131042.1)	(131514.6)
ΔHistSwt16$_t$	27132.6	51058.6	34473.6	59971.5	66405.7	70084.9	47461.6	40256.9
	(136897.7)	(136597.6)	(138411.5)	(131247.4)	(133073.8)	(138172.1)	(139717.8)	(132236.6)
ΔHistElite8$_t$	-57027.0	-37887.0	-79264.1	-49440.4	-56036.6	-67480.2	-98448.3	-86627.6
	(147449.0)	(146422.6)	(150858.8)	(142602.6)	(144040.1)	(146066.3)	(152677.4)	(154122.2)
ΔHistFin4$_t$	279799.6	313592.9	305928.5	414293.9	271937.7	259408.1	305566.7	280406.5
	(309776.9)	(319021.0)	(312481.2)	(324415.5)	(304535.8)	(305471.3)	(310948.4)	(307718.3)
ΔHistFinal$_t$	-334486.4	-127561.5	-224075.7	-186329.9	-183194.0	-195981.4	-184229.5	-199755.6
	(389581.6)	(348778.4)	(366984.8)	(388185.9)	(364808.2)	(352818.8)	(365163.4)	(350848.3)
ΔHistWinner$_t$	-743118.3	-927335.4	-803576.4	-771712.5	-779762.2	-767436.4	-782459.0	-841295.0

	(915554.8)	(955214.7)	(948226.0)	(921832.3)	(925451.0)	(939362.4)	(929336.6)	(919229.2)
ΔDistance$_t$	-542.4	-644.9	-564.8	-965.8	-709.6	-605.0	-805.9	-798.3
	(1593.3)	(1609.2)	(1580.1)	(1608.1)	(1608.9)	(1606.4)	(1594.4)	(1611.1)
ΔUndergradPop$_t$	-55864.5	-61866.8*	-51539.0	-53419.3	-57538.9*	-54363.7	-46457.9	-49147.5
	(36025.5)	(33932.3)	(35210.2)	(34036.0)	(33228.6)	(34187.3)	(35479.7)	(32878.2)
ΔPerCapPI$_t$	33299.8	29647.5	31822.9	20864.5	34637.8	36597.4	30895.9	33977.7
	(37835.7)	(37240.4)	(37232.4)	(37455.8)	(37624.8)	(37588.8)	(37399.5)	(37107.0)
ΔGrPerCapPI$_t$	15090.8	15783.0	17005.9	19979.8	15119.9	16022.8	15992.7	15724.9
	(14224.3)	(14418.7)	(14487.8)	(14645.9)	(14166.1)	(14133.0)	(14399.1)	(14201.0)
ΔCityPop$_t$	813343.7	960690.9	834331.9	747303.2	1089339.7	1051517.3	624404.9	642793.3
	(1759133.0)	(1717367.4)	(1730453.9)	(1651766.4)	(1705043.0)	(1709831.5)	(1727711.7)	(1709668.1)
ΔStatePop$_t$	103214.9	222000.4	272023.5	310423.6	302706.0	300106.8	274197.9	296181.1
	(376536.0)	(345488.2)	(354413.4)	(352520.8)	(351630.2)	(350233.0)	(353222.9)	(358030.8)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2819	2819	2819	2819	2819	2819	2819	2819
R^2	0.103	0.101	0.095	0.107	0.096	0.097	0.095	0.101
F-Stat	0.0575	3.149	0.504	2.131	0.707	1.758	0.499	0.558
P-Value	0.811	0.0771	0.478	0.145	0.401	0.186	0.480	0.456

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 61

Marginal Revenue of Winning a Basketball Game. This table reports fixed effects estimates of the marginal revenue of basketball team wins from Model (2.7) over the sample period 2003-2012.

	Program Revenue	
Wins	18451.6***	(4378.1)
$Wins_{t-1}$	4659.5	(4669.1)
$Wins_{t-2}$	16436.2***	(4713.7)
$CoachCarTourn_{t-1}$	54184.5***	(16246.8)
$CoachCareer_{t-1}$	-72184.7	(297230.3)
CoachChange	20731.5	(61281.9)
$NCAATourn_{t-1}$	164562.8**	(73893.8)
$Round2_{t-1}$	-62584.3	(128861.9)
$Sweet16_{t-1}$	295672.6*	(170950.7)
$Elitet8_{t-1}$	-66536.0	(450841.8)
$Final4_{t-1}$	408528.8	(380143.9)
$Final_{t-1}$	-33387.1	(270810.3)
$Champ_{t-1}$	1866059.7***	(621434.4)
NSchlsConf	4725.3	(40379.4)
NSchlsConfAP	-44714.4	(40760.6)
NSchlsConfTourn	3778.8	(39181.9)
NSchlsConfFF	-94229.6	(81111.3)
SOS	2833.8	(12194.3)
HistWins	-1764.6	(2928.0)
HistNCAATrn	-33022.4	(58785.5)
HistRound2	-71070.3	(111163.3)
HistSweet16	-98047.8	(145989.8)
HistElite8	119522.2	(194549.7)
HistFinal4	289881.7	(319786.8)
HistFinal	141240.8	(588022.9)
HistChamp	-829580.6	(792166.4)
Distance	-1086.2	(1539.2)
UndergradPop	-48837.7	(38063.6)
PerCapPI	12547.1	(39852.3)
GrPerCapPI	9334.8	(15435.1)
CityPop	802241.6	(1910127.9)
StatePop	50491.1	(418001.9)
Team Fixed Effects	Yes	
Year Fixed Effects	Yes	
Confr. Fixed Effects	Yes	

N	2820
Within R^2	0.670
Marginal Product	8.174

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 62

Marginal Revenue Product of Star College Football Players With Media Exposure Interactions. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.8) over the sample period 2003-2012. The variable *NewsHits* captures a team's media exposure and is measured by the number of media articles mentioning the football team in a given year. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
Stars	1527847.0**	4633685.3**	2311160.9**	283874.9
	(592293.1)	(2171812.6)	(1018131.7)	(268901.5)
News Hits	1260.6***	1084.3***	1047.0**	811.2**
	(472.7)	(390.1)	(401.2)	(405.0)
Star×NewsHits	-305.9	-1152.3**	-534.9*	149.7
	(205.0)	(571.6)	(320.6)	(171.3)
Stars_{t-1}	656178.3	1443532.2*	2069323.9***	394184.5*
	(408542.9)	(766749.5)	(648624.0)	(212148.4)
Stars_{t-2}	610146.0	-52440.1	200107.1	-27675.7
	(409370.9)	(629591.7)	(492664.2)	(187548.1)
Wins_{t-1}	-58770.7	-22780.3	-92091.8	-7950.2
	(106170.9)	(97190.8)	(103520.7)	(102070.0)
Wins_{t-2}	54694.8	107594.5*	87616.7	108449.8
	(55605.6)	(61775.8)	(62151.0)	(66117.6)
CoachCareer_{t-1}	2339675.1	1621998.3	2217796.3	1307032.6
	(2045885.0)	(2027532.5)	(2053493.2)	(2017477.9)
CoachChange	-117218.9	-68692.2	-93433.2	-34050.5
	(314723.8)	(297139.0)	(300646.0)	(314094.0)
BowlGame_{t-1}	832412.8*	702335.0	826800.1*	647347.9
	(462162.7)	(434767.6)	(454843.2)	(452718.4)
BowlWin_{t-1}	-323201.5	-257157.9	-198700.0	-359446.5
	(407543.8)	(417412.3)	(395952.0)	(418356.1)
SOS	-11039.8	124.0	-5667.0	16229.7
	(53030.1)	(58149.3)	(56795.6)	(57044.3)
TDPts		-32425.7	-25783.4	-29444.2

		(75466.2)	(71175.9)	(74917.3)
TDYds		1258287.9	1367952.7	945734.5
		(2862584.7)	(2914654.0)	(2973556.5)
TDPassYds		-1255423.6	-1365482.6	-943855.2
		(2863167.6)	(2915489.0)	(2974577.2)
TDPassTDs		-939128.9	-875102.6	-969194.7
		(764527.5)	(756904.7)	(754886.9)
TDRushYds		-1252121.1	-1363012.4	-941362.6
		(2862315.2)	(2914503.1)	(2973592.7)
TDRushTDs		80470.7	59253.4	72260.1
		(635488.2)	(609356.7)	(640994.8)
HistWins	-12057.6	-10630.2	-8393.3	-19576.1
	(47851.8)	(50734.3)	(50579.2)	(51194.0)
HistBowls	-566957.6	-571202.9	-542685.6	-535363.4
	(352943.0)	(367792.8)	(363931.3)	(364701.0)
HistBowlWins	431837.6	367572.6	332935.5	471647.9
	(428699.3)	(444457.2)	(437196.4)	(449091.5)
Distance	-23699.3	-22474.0	-23263.5	-19462.8
	(16502.9)	(16964.0)	(16887.1)	(17139.7)
UndergradPop	-118826.1	-153796.2	-176927.6	-157810.9
	(201994.2)	(204239.6)	(201006.7)	(198825.1)
PerCapPI	168200.5	241221.7	244011.9	202068.8
	(307982.0)	(327805.6)	(318255.4)	(321929.4)
GrPerCapPI	25505.0	23641.4	18780.0	8860.3
	(127285.8)	(125230.2)	(124645.6)	(129938.1)
CityPop	20139116.1	5160507.1	4868070.5	3167093.7
	(25406185.5)	(31856067.9)	(29240474.6)	(30301661.0)
StatePop	-775902.2	-100550.6	-301018.3	-70724.3
	(3974229.0)	(4039599.5)	(4104705.0)	(4001179.3)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040
Within R^2	0.777	0.779	0.782	0.778
Adjusted R^2	0.972	0.972	0.973	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 63

Marginal Revenue Product of Star College Football Players as a Function of the Team's Media Exposure. This table reports the marginal effects from the regressions in Table 62 for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Standard errors are in parentheses and have been computed using the delta method. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. This table reports the estimates that are displayed in Figure 3.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
1st Percentile: News Articles	1520198.5***	4604877.6**	2297789.5**	287617.6
	(588860.3)	(2158927.4)	(1011577.1)	(267338.2)
5th Percentile: News Articles	1495111.6***	4510388.3**	2253931.4**	299893.4
	(577776.7)	(2116790.6)	(990228.7)	(262636.0)
10th Percentile: News Articles	1477367.2***	4443554.4**	2222909.9**	308576.2
	(570106.3)	(2087108.3)	(975274.2)	(259717.9)
25th Percentile: News Articles	1431629.6***	4271284.3**	2142949.2**	330957.1
	(551026.1)	(2011099.4)	(937328.2)	(253841.1)
Median: News Articles	1341378.0***	3931353.4**	1985167.1**	375120.1
	(516652.3)	(1863516.0)	(865360.4)	(249659.4)
Mean: News Articles	1245116.0**	3568784.5**	1816877.5**	422224.1*
	(485640.1)	(1710394.1)	(793841.3)	(256351.7)
75th Percentile: News Articles	1170358.8**	3287213.0**	1686183.5**	458805.1*
	(466312.1)	(1595330.9)	(743010.4)	(268991.7)
90th Percentile: News Articles	880788.9**	2196553.2*	1179943.9*	600500.8*
	(439935.8)	(1199983.4)	(604392.6)	(362175.9)
95th Percentile: News Articles	627472.5	1242441.9	737084.5	724456.5
	(484124.1)	(976316.6)	(594033.9)	(475144.1)
99th Percentile: News Articles	134607.0	-613926.7	-124565.9	965631.1
	(692054.4)	(1135667.6)	(855844.7)	(724684.0)
N	1040	1040	1040	1040

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 64

Marginal Revenue Product of Star College Football Players With Media Exposure Interactions by Position. This table reports fixed effects estimates of a star football player's marginal revenue product from Model (2.9) over the sample period 2003-2012. The variable *NewsHits* captures a team's media exposure and is measured by the number of media articles mentioning the football team in a given year. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for six different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. The last two measures (5-6) are Top 10 in offensive touchdowns or yards for Running Backs and Wide Receivers. The difference between (4,5,6) is how star Quarterbacks are measured with (5) being a Top 10 Quarterback in pass efficiency rating (PER) or touchdowns or yards while (6) is a Top 10 Quarterback in pass efficiency rating alone.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
Star QB	5332184.3**	6022057.7**	2227635.3	458146.7
	(2459216.1)	(2936698.6)	(1763110.4)	(617663.4)
Star RB	1893386.0	7346421.2***	3110843.8	743821.2
	(1683276.1)	(2331204.1)	(2016302.9)	(544053.1)
Star WR	5033484.0**	-3008518.8	7164596.3*	-380705.7
	(2424484.2)	(5474681.1)	(3929266.1)	(446168.5)
News Hits	1105.4**	928.8**	1034.6**	900.6**
	(472.6)	(381.8)	(404.5)	(388.0)
StarQB×NewsHits	-559.0	-1026.5	-347.0	112.9
	(763.3)	(756.5)	(491.2)	(352.3)
StarRB×NewsHits	-927.6	-2763.8***	-1280.2*	-351.1
	(696.4)	(936.7)	(741.3)	(353.9)
StarWR×NewsHits	-1186.0	673.1	-2345.2	722.8
	(776.7)	(2485.1)	(1700.2)	(505.2)
Star TE	878247.4			
	(1172084.3)			
Star OL	1533496.0			
	(2089403.0)			
Star K	-1182293.1			
	(788807.7)			
Star P	2299127.3			
	(2407059.2)			
Star LB	1005372.0			
	(1219271.2)			
Star DB	370359.9			
	(919084.2)			
Star DL	-492170.5			
	(1099973.4)			
Star QB_{t-1}	2685964.4	1714592.1*	2850792.1***	419844.1
	(2172106.3)	(1009546.0)	(856200.4)	(507064.7)
Star RB_{t-1}	512294.6	1164631.7	587157.8	455831.5

	(1361063.5)	(1565306.9)	(1153191.6)	(440201.5)
Star WR$_{t-1}$	2261409.7	-82343.4	3329514.0	264635.8
	(1414959.2)	(2748815.0)	(2117586.8)	(406324.4)
Star TE$_{t-1}$	1588584.9			
	(977471.9)			
Star OL$_{t-1}$	-710863.9			
	(1965691.0)			
Star K$_{t-1}$	-1997853.1			
	(1280828.5)			
Star P$_{t-1}$	640109.0			
	(1353522.6)			
Star DL$_{t-1}$	-1022854.1			
	(1158229.3)			
Star LB$_{t-1}$	-452561.8			
	(862596.8)			
Star DB$_{t-1}$	1261088.6			
	(1094766.0)			
Star QB$_{t-2}$	152973.5	1139158.5	1264182.2**	308399.3
	(1722587.8)	(854272.2)	(614252.3)	(508275.4)
Star RB$_{t-2}$	-269915.1	-1779313.2	-1556697.8	-294616.2
	(995989.1)	(1429351.4)	(950286.8)	(444607.2)
Star WR$_{t-2}$	1232381.7	-1681622.1	763024.3	49862.2
	(882645.8)	(2122625.7)	(1335241.8)	(396092.9)
Star TE$_{t-2}$	2435922.7			
	(1859375.8)			
Star OL$_{t-2}$	-372205.3			
	(1648809.0)			
Star K$_{t-2}$	-1177121.6			
	(1338451.1)			
Star P$_{t-2}$	-1166057.2			
	(1444158.0)			
Star DL$_{t-2}$	693310.1			
	(1263470.6)			
Star LB$_{t-2}$	970667.6			
	(1381379.3)			
Star DB$_{t-2}$	1146414.6			
	(999671.8)			
Wins$_{t-1}$	-76645.4	-16783.0	-107737.8	-3898.1
	(108166.0)	(98638.7)	(107062.5)	(109253.0)
Wins$_{t-2}$	43306.5	109015.6*	79831.0	104538.3
	(56167.1)	(63068.6)	(64771.7)	(71464.3)
CoachCareer$_{t-1}$	3000223.6	1673765.4	2383259.1	1329643.4
	(2101270.3)	(1999507.2)	(2056283.0)	(2077973.7)
CoachChange	-147900.4	-43539.1	-103611.1	25132.9
	(305778.7)	(297695.4)	(309014.1)	(323062.5)
BowlGame$_{t-1}$	758473.0*	697892.6	851781.7*	637465.1
	(431070.2)	(432396.9)	(463519.1)	(457367.3)
BowlWin$_{t-1}$	-301992.0	-281157.6	-186185.9	-336725.6
	(383750.5)	(422520.3)	(395540.3)	(418792.9)
SOS	14189.8	6692.6	10587.0	12519.5

	(52582.6)	(59661.2)	(58461.6)	(57942.2)
TDPts		-37907.8	-28048.6	-26072.8
		(76065.1)	(70924.8)	(75743.3)
TDYds		1274005.5	1166833.7	732467.6
		(2871222.9)	(2932863.2)	(2921513.5)
TDPassYds		-1270975.1	-1164529.5	-730395.0
		(2871748.5)	(2933650.3)	(2922461.0)
TDPassTDs		-972605.6	-879431.2	-980479.1
		(772462.0)	(757462.8)	(738680.4)
TDRushYds		-1267421.7	-1161220.7	-728254.2
		(2871061.7)	(2932642.1)	(2921521.3)
TDRushTDs		108586.5	77624.3	73206.7
		(635161.7)	(618244.8)	(640767.3)
HistWins	-15869.2	-19892.5	-22199.9	-20833.8
	(49866.7)	(51182.5)	(51037.6)	(49678.3)
HistBowls	-585951.3	-523087.7	-480686.4	-531257.6
	(378029.8)	(362290.3)	(365162.9)	(346037.8)
HistBowlWins	457912.6	426048.5	422671.4	515111.3
	(451677.3)	(442259.4)	(445961.0)	(447398.9)
Distance	-19826.5	-18412.2	-20893.0	-17135.8
	(17510.2)	(17320.1)	(16896.6)	(16817.1)
UndergradPop	-119577.8	-147548.5	-203113.1	-149713.3
	(210509.7)	(205176.0)	(206885.1)	(201870.7)
PerCapPI	66131.6	234402.9	225447.9	186953.2
	(283358.4)	(330892.0)	(319379.2)	(324312.1)
GrPerCapPI	23690.8	20461.6	20490.8	10166.1
	(125383.0)	(126776.8)	(125181.9)	(131038.8)
CityPop	7253527.8	11305331.5	7790789.6	4139477.1
	(28662474.4)	(34187086.2)	(29655178.0)	(29338509.5)
StatePop	-1114556.5	153169.4	-189221.4	-136208.9
	(3579536.0)	(4076199.6)	(4177540.6)	(3986050.2)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes
N	1040	1040	1040	1040
Within R^2	0.788	0.783	0.786	0.779
Adjusted R^2	0.973	0.973	0.973	0.972

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 65

Marginal Revenue Product of Star College Quarterbacks as a Function of the Team's Media Exposure. This table reports the marginal effects for Quarterbacks from the regressions in Table 64 for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Standard errors are in parentheses and have been computed using the delta method. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. This table reports the estimates that are displayed in Figure 5.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
1st Percentile: News Articles	5318210.5**	5996394.2**	2218960.1	460969.2
	(2442394.8)	(2919788.6)	(1752356.1)	(611816.7)
5th Percentile: News Articles	5272376.5**	5912217.9**	2190505.3	470227.0
	(2387460.0)	(2864499.5)	(1717225.8)	(593152.8)
10th Percentile: News Articles	5239957.3**	5852678.6**	2170378.8	476775.2
	(2348835.0)	(2825561.7)	(1692516.1)	(580457.3)
25th Percentile: News Articles	5156394.1**	5699210.8**	2118501.0	493653.7
	(2250235.6)	(2725887.7)	(1629394.5)	(549886.1)
Median: News Articles	4991503.4**	5396381.3**	2016133.3	526959.2
	(2060380.8)	(2532515.5)	(1507584.8)	(500457.8)
Mean: News Articles	4815631.7***	5073384.8**	1906948.4	562482.7
	(1866560.9)	(2332136.1)	(1382585.2)	(467851.9)
75th Percentile: News Articles	4679049.6***	4822545.3**	1822155.3	590070.3
	(1724110.0)	(2181745.0)	(1289938.9)	(459689.8)
90th Percentile: News Articles	4150002.1***	3850924.8**	1493711.3	696930.1
	(1283772.9)	(1665987.1)	(988372.6)	(567315.6)
95th Percentile: News Articles	3687190.3***	3000949.3**	1206387.8	790411.3
	(1159980.1)	(1371225.3)	(854641.4)	(775145.9)
99th Percentile: News Articles	2786719.6	1347192.7	647356.4	972293.2
	(1745418.4)	(1544953.0)	(1095029.7)	(1277199.5)
N	1040	1040	1040	1040

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 66

Marginal Revenue Product of Star College Wide Receivers as a Function of the Team's Media Exposure. This table reports the marginal effects for Wide Receivers from the regressions in Table 64 for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Standard errors are in parentheses and have been computed using the delta method. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. This table reports the estimates that are displayed in Figure 6.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
1st Percentile: News Articles	5003833.5**	-2991691.6	7105967.0*	-362636.1
	(2408114.7)	(5422487.7)	(3891184.4)	(439785.3)
5th Percentile: News Articles	4906579.9**	-2936498.5	6913662.7*	-303367.7
	(2354748.1)	(5252811.0)	(3766940.7)	(420833.7)
10th Percentile: News Articles	4837790.7**	-2897459.5	6777642.6*	-261446.2
	(2317315.8)	(5134293.7)	(3679717.6)	(409434.7)
25th Percentile: News Articles	4660480.6**	-2796833.0	6427039.2*	-153389.8
	(2222134.5)	(4835226.1)	(3457716.3)	(388791.2)
Median: News Articles	4310604.6**	-2598272.3	5735213.0*	59831.9
	(2040686.6)	(4278536.8)	(3034504.9)	(390008.3)
Mean: News Articles	3937428.3**	-2386488.4	4997314.2*	287253.2
	(1858797.1)	(3752215.1)	(2613843.5)	(449522.0)
75th Percentile: News Articles	3647619.1**	-2222016.7	4424261.0*	463868.9
	(1728207.5)	(3411771.5)	(2319871.6)	(525100.2)
90th Percentile: News Articles	2525050.8*	-1584939.9	2204554.1	1147985.2
	(1360957.6)	(3025560.3)	(1738433.0)	(921246.6)
95th Percentile: News Articles	1543025.9	-1027623.9	262750.4	1746451.4
	(1321392.3)	(4006629.3)	(2281514.3)	(1313348.4)
99th Percentile: News Articles	-367653.1	56719.1	-3515324.2	2910858.5
	(1977335.4)	(7330911.3)	(4561965.4)	(2105319.9)
N	1040	1040	1040	1040

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 67

Marginal Revenue Product of Star College Running Backs as a Function of the Team's Media Exposure. This table reports the marginal effects for Runningbacks from the regressions in Table 64 for various percentiles of media exposure, as measured by the number of media articles mentioning the football team, over the sample period 2003-2012. Standard errors are in parentheses and have been computed using the delta method. Estimates for four different measures of star player are reported: (1) All Americans, (2) Heisman Finalists (voted 5th place or above), (3) Heisman Nominees, and (4) Top 10 in offensive touchdowns or yards. This table reports the estimates that are displayed in Figure 5.

	(1) AA Team	(2) HF	(3) HN	(4) TDYds
1st Percentile: News Articles	1870197.0	7277325.7***	3078838.3	735044.1
	(1666992.0)	(2310349.7)	(1999583.3)	(538541.4)
5th Percentile: News Articles	1794136.9	7050692.4***	2973860.3	706255.3
	(1613745.1)	(2242302.5)	(1944973.4)	(521108.8)
10th Percentile: News Articles	1740338.3	6890390.9***	2899607.6	685892.5
	(1576245.7)	(2194521.0)	(1906572.5)	(509416.6)
25th Percentile: News Articles	1601667.9	6477199.8***	2708214.8	633405.5
	(1480289.5)	(2072848.1)	(1808544.4)	(482009.0)
Median: News Articles	1328037.1	5661872.9***	2330550.0	529835.9
	(1294646.4)	(1840436.1)	(1619956.2)	(441742.1)
Mean: News Articles	1036183.8	4792248.7***	1927734.5	419369.1
	(1104392.1)	(1607937.0)	(1428295.7)	(423656.4)
75th Percentile: News Articles	809530.0	4116897.5***	1614907.4	333580.4
	(965123.3)	(1443150.4)	(1288942.2)	(429460.1)
90th Percentile: News Articles	-68407.2	1500941.8	403179.7	1280.1
	(601397.0)	(1060292.1)	(902224.1)	(587171.3)
95th Percentile: News Articles	-836428.4	-787501.2	-656842.0	-289416.9
	(758802.0)	(1254993.1)	(938130.5)	(817944.8)
99th Percentile: News Articles	-2330730.6	-5240015.3**	-2719275.5	-855012.0
	(1702317.0)	(2428964.0)	(1779810.5)	(1338658.7)
N	1040	1040	1040	1040

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 68

Marginal Revenue Product of Star College Basketball Players With Media Exposure Interactions. This table reports estimates of a star basketball player's marginal revenue product from Model (2.8) over the sample period 2003-2012. The variable *NewsHits* captures a team's media exposure and is measured by the number of media articles mentioning the basketball team in a given year. Revenues are real 2012 USD at an annual frequency. Standard errors are in parentheses and have been clustered by team. Estimates for eight different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team and (4) NBA Drafted Players.

	(1) AW	(2) AAFt	(3) AA	(4) Drafted
Stars	588472.6	395654.3	-93061.5	232661.0**
	(849430.7)	(324183.3)	(328625.0)	(114617.1)
Stars_{t-1}	157025.1	15131.3	112783.4	9315.8
	(379744.4)	(287768.8)	(173239.5)	(92096.2)
Stars_{t-2}	200920.0	167969.9	201555.6	235651.1**
	(328418.7)	(221090.4)	(154874.8)	(101868.2)
News Hits	446.7***	444.2**	448.2**	583.0***
	(159.8)	(182.8)	(205.7)	(206.6)
Stars×NewsHits	122.5	11.28	163.7	-109.8
	(610.6)	(177.7)	(209.1)	(94.54)
Wins_{t-1}	4537.3	3999.5	3813.1	5279.3
	(4682.2)	(4623.6)	(4638.1)	(4573.3)
Wins_{t-2}	12346.3***	11819.3***	11104.2**	8178.9*
	(4321.2)	(4395.5)	(4359.1)	(4619.7)
$\text{CoachCarTourn}_{t-1}$	52528.2***	52526.3***	52217.8***	51623.5***
	(16288.0)	(16347.0)	(16529.8)	(16371.7)
CoachCareer_{t-1}	-67393.3	-31969.4	-41421.6	-54890.4
	(295827.2)	(293222.0)	(295276.0)	(290423.7)
CoachChange	9487.0	7056.4	10431.8	12642.0
	(61218.2)	(61286.2)	(60971.1)	(61058.9)
NCAATourn_{t-1}	155183.0**	156048.0**	159387.6**	158003.4**
	(74734.8)	(75034.6)	(73998.4)	(76073.5)
Round2_{t-1}	-75453.6	-68600.0	-66214.4	-71452.5
	(127022.9)	(124950.7)	(128181.3)	(129267.9)
Sweet16_{t-1}	235718.6	237722.4	234165.7	276679.6
	(170321.1)	(178978.1)	(173296.2)	(169804.0)
Elitet8_{t-1}	-147538.5	-155104.1	-150278.0	-47642.5
	(455950.8)	(456147.8)	(467063.7)	(424085.1)
Final4_{t-1}	294967.2	295383.8	309361.9	391479.5
	(387936.7)	(383458.8)	(379385.0)	(401090.3)
Final_{t-1}	-113990.8	-64720.5	-125992.1	-49994.4
	(309674.1)	(363908.5)	(347783.4)	(327206.6)
Champ_{t-1}	1773324.1**	1873470.1***	1856519.0***	2079244.7***
	(858311.9)	(610972.8)	(678905.9)	(655752.8)
NSchlsConf	1578.5	844.9	925.8	472.5
	(40030.2)	(39915.3)	(39437.2)	(40515.0)

NSchlsConfAP	-53395.3	-54596.2	-55297.0	-50798.8
	(39588.2)	(41279.3)	(40506.7)	(41024.4)
NSchlsConfTourn	-72.31	-140.0	-269.2	-6971.3
	(40178.3)	(40065.3)	(40039.8)	(38525.9)
NSchlsConfFF	-120766.3	-116491.7	-114384.4	-103640.9
	(83418.8)	(82859.5)	(83514.2)	(84102.1)
SOS	-4199.6	-4821.7	-5255.2	-6439.6
	(12317.7)	(12394.2)	(12471.3)	(12502.9)
HistWins	-2963.0	-3047.8	-3193.1	-3296.0
	(2908.1)	(2913.6)	(2910.5)	(2923.7)
HistNCAATrn	-21079.7	-20178.6	-19123.2	-33086.6
	(58438.0)	(59883.5)	(60071.3)	(58375.0)
HistRound2	-63994.4	-47475.1	-53692.2	-42805.8
	(109256.3)	(111212.1)	(112508.3)	(109715.0)
HistSweet16	-116742.0	-114420.6	-95267.2	-72617.8
	(144241.1)	(142943.8)	(137927.0)	(134728.7)
HistElite8	113112.5	123497.9	126328.6	153465.9
	(178719.2)	(184541.0)	(184250.4)	(179517.0)
HistFinal4	289992.4	357069.9	392826.7	418482.5
	(322075.7)	(317900.1)	(328469.4)	(326402.8)
HistFinal	121801.5	226104.2	226640.5	207799.0
	(599612.6)	(592969.7)	(597996.7)	(578786.7)
HistChamp	-705770.9	-775991.9	-748345.7	-713955.6
	(845244.3)	(795785.6)	(797703.6)	(781527.7)
Distance	-748.6	-671.7	-673.9	-768.7
	(1569.4)	(1558.2)	(1583.2)	(1525.9)
UndergradPop	-47590.0	-45863.9	-47014.3	-43557.0
	(38776.8)	(37715.5)	(38401.7)	(39003.7)
PerCapPI	18195.3	16484.9	15493.5	8589.7
	(40359.3)	(39882.0)	(39224.3)	(39652.7)
GrPerCapPI	6879.7	8177.3	8356.7	10353.4
	(15567.2)	(15527.1)	(15363.5)	(15616.5)
CityPop	847637.3	889131.5	877856.8	779643.1
	(1845638.1)	(1816622.7)	(1827867.8)	(1851544.0)
StatePop	-149.1	43559.0	18591.8	56614.8
	(432716.0)	(412377.8)	(419491.4)	(436959.5)
Team Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Confr. Fixed Effects	Yes	Yes	Yes	Yes
N	2820	2820	2820	2820
Within R^2	0.673	0.672	0.672	0.675
Adjusted R^2	0.969	0.969	0.969	0.969

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 69

Marginal Revenue Product of Star College Basketball Players as a Function of the Team's Media Exposure. This table reports the marginal effects from the regressions in Table 68 for various percentiles of media exposure, as measured by the number of media articles mentioning the basketball team, over the sample period 2003-2012. Standard errors are in parentheses and have been computed using the delta method. Estimates for four different measures of star player are reported: (1) Wooden Award Winner, Naismith Award Winner or the NCAA Tournament's Most Outstanding Player, (2) All American First Team, (3) All American First or Second Team, and (4) NBA Drafted Players. This table reports the estimates that are displayed in Figure 4.

	(1) AW	(2) AAFt	(3) AA	(4) Drafted
1st Percentile: News Articles	588962.5	395699.4	-92406.7	232221.9**
	(847323.6)	(323621.7)	(327938.5)	(114371.4)
5th Percentile: News Articles	590799.9	395868.5	-89951.3	230575.6**
	(839437.9)	(321520.9)	(325370.6)	(113456.4)
10th Percentile: News Articles	592147.3	395992.6	-88150.7	229368.2**
	(833671.7)	(319985.6)	(323493.8)	(112792.0)
25th Percentile: News Articles	595454.5	396297.0	-83730.9	226404.7**
	(819579.6)	(316237.0)	(318910.7)	(111185.7)
Median: News Articles	602191.4	396917.2	-74727.7	220368.0**
	(791159.9)	(308690.7)	(309683.1)	(108026.4)
Mean: News Articles	619777.6	398536.3	-51225.4	204609.4**
	(719073.9)	(289620.5)	(286370.9)	(100581.2)
75th Percentile: News Articles	622892.0	398823.0	-47063.3	201818.7**
	(706675.4)	(286347.9)	(282374.6)	(99397.9)
90th Percentile: News Articles	668580.5	403029.2*	13994.8	160878.6*
	(543578.6)	(242976.9)	(229972.5)	(87958.2)
95th Percentile: News Articles	707042.0	406570.0*	65394.9	126414.3
	(451946.3)	(215697.5)	(199287.0)	(88658.4)
99th Percentile: News Articles	835900.6	418433.0*	237601.5	10947.8
	(659140.2)	(223596.4)	(241659.1)	(145320.2)
N	2820	2820	2820	2820

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

BIBLIOGRAPHY

A. B. Abel. Asset prices under habit formation and catching up with the joneses. *American Economic Review*, 80(2):38–42, May 1990.

A. B. Abel. Risk premia and term premia in general equilibrium. *Journal of Monetary Economics*, 43:3–33, 1999.

M. J. Álvarez Peláez and A. Díaz. Minimum consumption and transitional dynamics in weath distribution. *Journal of Monetary Economics*, 52:633–667, 2005.

A. Atkeson and M. Ogaki. Wealth-varying intertemporal elasticity of substitution: Evidence from panel and aggregate data. *Journal of Monetary Economics*, 38:507–534, 1996.

A. Atkeson and M. Ogaki. Rate of time preference, intertemporal elasticity of substitution, and level of wealth. *The Review of Economics and Statistics*, 79(4):564–572, November 1997.

O. P. Attanasio and M. Browning. Consumption over the life cycle and over the business cycle. *American Economic Review*, 85(5):1118–1137, December 1995.

O. P. Attanasio and G. Weber. Intertemporal substitution, risk aversion and the euler equation for consumption. *The Economic Journal*, 99:59–73, 1989.

D. K. Backus, A. W. Gregory, and S. E. Zin. Risk premiums in the term structure, evidence from artificial economies. *Journal of Monetary Economics*, 24:371–399, 1989.

R. Bansal and A. Yaron. Risks for the long-run: A potential resolution of asset pricing puzzles. *Journal of Finance*, 59(4):1481–1509, 2004.

R. Bansal, D. Kiku, and A. Yaron. An empirical evaluation of the long-run risks model for asset prices. *Critical Finance Review*, 1:183–221, 2012.

N. Barberis, M. Huang, and T. Santos. Prospect theory and asset prices. *Quarterly Journal of Economics*, 116(1):1–53, February 2001.

R. J. Barro. Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, 121:823–866, August 2006.

P. Beaudry and E. V. Wincoop. The intertemporal elasticity of substitution: An exploration using a panel of state data. *Economeica*, 63(251):495–512, August 1996.

J. Beeler and J. Y. Campbell. The long-run risks model and aggregate asset prices: An empirical assesment. *Critical Finance Review*, 1:141–182, 2012.

D. J. Berri and R. Simmons. Catching a draft: on the process of selecting quarterbacks in the national football league amatuer draft. *Journal of Productivity Analysis*, 35:37–49, 2011.

R. W. Brown. An estimate of the rent generated by a premium college football player. *Economic Inquiry*, pages 671–684, October 1993.

R. W. Brown. Measuring cartel rents in the college basketball player recruitment market. *Applied Economics*, 26:27–34, 1994.

R. W. Brown. Research note: Estimates of college football player rents. *Journal of Sports Economics*, 12(2):200–212, 2011.

R. W. Brown. Do nfl player earnings compensate for monopsony exploitation in college? *Journal of Sports Economics*, 13(4):393–405, 2012.

R. W. Brown and R. T. Jewell. *Economics of College Sports*, chapter Measuring Marginal Revenue Product in College Athletics: Updated Estimates. Praeger, Westport, Connecticut, 2004.

R. W. Brown and R. T. Jewell. The marginal revenue product of a women's college basketball player. *Industrial Relations*, 45(1):96–101, January 2006.

J. Campbell and A. Deaton. Why is consumption so smooth? *The Review of Economic Studies*, 56(3):357–373, July 1989.

J. Y. Campbell. Bond and stock returns in a simple exchange model. *Quarterly Journal of Economics*, 101(4):785–804, November 1986.

J. Y. Campbell. Asset prices, consumption and the business cycle. In J. B. Taylor and M. Woodford, editors, *Handbook of Macroeconomics*, volume 1, chapter 19, pages 1231–1303. Elsevier Science, 1999.

J. Y. Campbell. *Handbook of the Economics of Finance*, volume 1, chapter Consumption-based Asset Pricing, pages 803–887. Elsevier Science, North-Holland, Amsterdam, The Netherlands, 2003.

J. Y. Campbell and J. H. Cochrane. By force of habit: a consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107:205–251, April 1999.

J. Y. Campbell and G. N. Mankiw. *National Bureau of Economic Research Macroeconomics Annual*, volume 4, chapter Consumption, Income and Interest Rates: Reinterpreting the Time Series Evidence, pages 185–246. MIT Press, 1989.

J. Y. Campbell and R. J. Shiller. The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228, 1988.

J. Y. Campbell, R. J. Shiller, and L. M. Viceira. Understanding inflation-indexed bond markets. *Brookings Papers on Economic Activity*, 1:79–120, Spring 2009.

C. L. Cavanagh, G. Elliot, and J. H. Stock. Inference in models with nearly integrated regressors. *Econometric Theory*, 11(5):1131–1147, December 1995.

R. Chou, R. F. Engle, and A. Kane. Measuring risk aversion from excess returns on a stock index. *Journal of Econometrics*, 52:201–224, 1992.

J. H. Cochrane and L. P. Hansen. *National Bureau of Economic Research Macroeconomics Annual*, volume 7, chapter Asset Pricing Lessons for Macroeconomics. MIT Press, 1992.

A. Cohn, J. Engelmann, E. Fehr, and M. Marechal. Evidence for countercyclical risk aversion: An experiment with financial professionals. *UBS Center Working Paper Series*, (4), 2013.

G. M. Constantinides. Habit formation: A resolution of the equity premium puzzle. *Journal of Political Economy*, 98(3):519–543, 1990.

T. F. Crossley and H. W. Low. Is the elasticity of intertemporal substitution constant? *Journal of The European Economic Association*, 9(1):87–105, February 2011.

J. Donaldson and R. Mehra. Risk based explinations of the equity premium. In R. Mehra, editor, *Handbook of the Equity Risk Premium*, chapter 2, pages 39–94. Elsevier Science, 2008.

J. M. Dumond, A. K. Lynch, and J. Platania. An economic model of the college football recruiting process. *Journal of Sports Economics*, 9(1):67–87, February 2008.

Edward C. O'Bannon v. National Collegiate Athletic Association. United States District Court For the Northern District of California. *4:09-cv-03329-CW*, 2014.

G. V. Engegelhardt and A. Kumar. The elasticity of intertemporal substitution: New evidence from 401(k) participation. *Economics Letters*, 103:15–17, 2009.

L. G. Epstein and S. E. Zin. Substitution, risk aversion and the temporal behavior of consumption and assets returns: A theoretical framework. *Econometrica*, 57(4):937–969, July 1989.

E. F. Fama. Forward and spot exchange rates. *Journal of Monetary Economics*, 14:319–338, 1984.

E. F. Fama and K. R. French. Dividend yields and expected stock returns. *Journal of Financial Economics*, 22:3–25, 1988.

E. F. Fama and K. R. French. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, 25:23–49, 1989.

X. Gabaix. Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *Quarterly Journal of Economics*, 127(2):645–700, March 2012.

M. Getz and J. Siegfried. *The Oxford Handbook of Sports Ecomics: The Economics of College Sports Volume 1*, chapter What Does Intercollegiate Athletics Do To Or For Colleges And Universities, pages 349–372. Oxford University Press, April 2012.

S. Gordon and P. St-Amour. A preference regime model of bull and bear markets. *American Economic Review*, 90(4):1019–1033, September 2000.

J. Gruber. A tax-based estimate of the elasticity of intertemporal substitution. NBER Working Paper 11945, 2006.

L. Guiso, P. Sapienza, and L. Zingales. Time-varying risk aversion. NBER Working Paper 19284, August 2013.

A. Guren, D. Manoli, A. Weber, and R. Chetty. Are micro and macro labor supply elasticities consistent? a review of evidence on the intensive and extensive margins. *American Economic Review Papers and Proceedings*, 101:471–75, May 2011.

F. Guvenen. Reconciling conflicting evidence on the elasticity of intertemporal substitution. *Journal of Monetary Economics*, 53:1451–1472, 2006.

F. Guvenen. A parsimonious macroeconomic model for asset pricing. *Econometrica*, 77(6): 1711–1750, November 2009.

J. Hahn and J. Hausman. Estimation with valid and invalid instruments. *Annales D'Economie ET DE Statistique*, (79):25–57, 2005.

R. E. Hall. Intertemporal substitution in consumption. *Journal of Political Economy*, 96 (2):339–357, April 1988.

L. P. Hansen and K. Singleton. Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica*, 50(5):1269–1286, September 1982.

C. R. Harvey. Time-varying conditional covariances in tests of asset pricing models. *Journal of Financial Economics*, 24:289–317, 1989.

T. Havranek, R. Horvath, Z. Irsova, and M. Rusnak. Cross-country heterogeneity in intertemporal substitution. Working Paper, August 2013.

R. J. Hodrick. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *The Review of Financial Studies*, 5(3):357–386, 1992.

R. Huma and E. J. Staurowsky. The price of poverty in big time college sports. Technical report, National Collge Players Association and Drexel University Sports Management, 2011.

R. Huma and E. J. Staurowsky. The $6 billion heist: Robbing college athletes under the guise of amatuerism. Technical report, National Collge Players Association and Drexel University Sports Management, 2012.

P. K. Hunsberger and S. R. Gitter. What is a blue chip recruit worth? estimating the marginal revenue product of college football quarterbacks. Towson University Department of Economics Working Paper No. 2014-03, April 2014.

R. A. Judson and A. L. Owen. Estimating dynamic panel data models: A guide for macroeconomists. *Economic Letters*, 65:9–15, May 1999.

C. Julliard and A. Ghosh. Can rare events explain the equity premium puzzle? *The Review of Financial Studies*, 25(10):3037–3076, 2012.

L. M. Kahn. Cartel behavior and amateurism in college sports. *Journal of Economic Perpectives*, 21(1):209–226, Winter 2007.

M. J. Kamstra, L. A. Kramer, M. D. Levi, and T. Wang. Seasonally varying preferences: Theoretical foundations for an empirical regularity. *Review of Asset Pricing Studies*, 4 (1):39–77, March 2014.

A. C. Krautmann. What's wrong with scully-estimates of a player's marginal revenue product. *Economic Inquiry*, 37(2):369–381, April 1999.

E. Lane, J. Nagel, and J. S. Netz. Alternative approaches to measuring mrp: Are all men's college basketball players exploited? *Journal of Sports Economics*, 15(3):237–262, 2014.

M. Lettau, S. Ludvigson, and J. A. Wachter. The declining equity premium: What role does macroeconomic risk play? *The Review of Financial Studies*, 21(4):1653–1687, July 2008.

Y. Li. Expected returns and habit persistence. *The Review of Financial Studies*, 14(3): 861–899, 2001.

G. F. Loewenstein. Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, 65(3):272–292, March 1996.

G. F. Loewenstein. Emotions in economic theory and economic behavior. *American Economic Review Papers and Proceedings*, 90(2):426–432, May 2000.

G. F. Loewenstein, E. U. Weber, C. K. Hsee, and N. Welch. Risk as feelings. *Psychological Bulletin*, 127(2):267–286, 2001.

R. E. Lucas. Asset prices in an exchange economy. *Econometrica*, 46(6):1429–1445, November 1978.

U. Malmendier and S. Nagel. Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics*, 126:373–416, 2011.

Martin Jenkins et al. v. National Collegiate Athletic Association et al. United States District Court District of New Jersey. *3:33-av-00001*, 2014.

R. Mehra and E. Prescott. The equity premium: A puzzle. *Journal of Monetary Economics*, 15:145–161, 1985.

A. Melino and A. X. Yang. State-dependent preferences can explain the equity premium puzzle. *Review of Economics Dynamics*, 6:806–830, 2003.

NCAA. *2013-2014 Division I Manual*. National Collegiate Athletic Association, P.O. Box 6222, Indianapolis IN 46206-6222, July 2013.

S. Nickell. Biases in dynamic models with fixed effects. *Econometrica*, 49(6):1417–1426, November 1981.

Northwesern University v. College Athletes Players Association. Unite States National Labor Relations Board Region 13. *13-RC-121359*, March 2014.

M. Piazzesi and M. Schneider. *National Bureau of Economic Research Macroeconomics Annual*, chapter Equilibrium Yield Curves. MIT Press, Cambridge, MA, 2006.

T. A. Rietz. The equity risk premium: A solution. *Journal of Monetary Economics*, 22: 117–131, 1988.

B. R. Routledge and S. E. Zin. Generalized disappointment aversion and asset prices. *The Journal of Finance*, 65(4):1303–1332, August 2010.

G. W. Scully. Pay and performance in major league baseball. *The American Economic Review*, 64(6):915–930, December 1974.

Sports Illustrated. NFL's average salaries by position, February 2013. URL http://www.si.com/nfl/photos/2013/01/31/nfl-average-salaries-position/1#1.

R. F. Stambaugh. Predictive regressions. *Journal of Financial Economics*, 54:375–421, 1999.

J. H. Stock, J. H. Wright, and M. Yogo. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics*, 20(4):518–529, October 2002.

R. D. Tollison. *The Oxford Handbook of Sports Ecomics: The Economics of College Sports Volume 1*, chapter To be or not to be, the NCAA as a cartel, pages 339–348. Oxford University Press, April 2012.

A. Vissing-Jorgensen. Limited asset market participation and the elasticity of intertemporal substitution. *Journal of Political Economy*, 110(4):825–853, August 2002.

J. A. Wachter. A consumption-based model of the term structure of interest rates. *Journal of Financial Economics*, 79:365–399, 2006.

J. A. Wachter. Can time-varying risk of rare disasters explain aggregate stock market volatility? *The Journal of Finance*, 68(3):987–1035, June 2013.

P. Weil. The equity premium puzzle and the risk free rate puzzle. *Journal of Monetary Economics*, 24:401–421, 1989.

C. Wesseling. Why are running backs paid like kickers, punters?, February 2014. URL http://www.nfl.com/news/story/0ap2000000337644/article/why-are-running-backs-paid-like-kickers-punters.

A. Zimbalist. *Diamonds are Forever: The Business of Baseball*, chapter Salaries and Performance: Beyond the Scully Model. Brookings Institution Pres, Washington DC, 1992.