A WINNING PROPOSITION: THE ECONOMIC IMPACT OF SUCCESSFUL NATIONAL FOOTBALL LEAGUE FRANCHISES

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Research has demonstrated that a Super Bowl victory increases the personal income of the individuals in the metropolitan area from which the winning teams come. We argue that the economic benefits should extend beyond just the championship team's city to the cities of teams that experience seasonal success, and thus, the winning percentages of National Football League teams were included in our model. When controlling for sources of bias, winning percentage of the local professional football team had a significant positive effect on real per capita personal income. Explanations for these conclusions are offered from a psychological perspective. (JEL L83, R19)

"It was the best of times and it was the worst of times." This classic phrase could be used to describe the period of 1990 through 1993 for fans of the Buffalo Bills. The Bills performed well enough to win the American Football Conference Championship four consecutive years, but each year the team's season ended with a Super Bowl defeat. The purpose of this study is to determine if fans of successful, but not world champion, sport teams (like the Buffalo Bills) experience economic benefits in conjunction with their team's successes.

Coates and Humphreys (2002) examined whether a sports team winning a championship had a positive effect on the real per capita personal income of the local metropolitan area. Despite examining various measures of success across several different sports,¹ Coates and Humphreys found that the local National Football League (NFL) team winning the

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1. The variables that Coates and Humphreys included for the NFL were making the play-offs, winning the conference championship, and winning the Super Bowl. The sports included were the NBA, the NFL, and MLB. Super Bowl was the only variable that had a significant positive effect on income. Although Matheson (2006) shows evidence contradicting the findings, Coates and Humphreys' results are interesting when considered in the context of other similar studies that fail to find a positive effect from the presence of the teams in the city (Coates and Humphreys 1999, 2003), the building of stadia for the teams (Coates and Humphreys 1999), or the presence of major events like the Super Bowl or World Cup (Baade and Matheson 2000, 2004; Matheson and Baade 2006) on local income. In this paper, we use a psychological framework to provide a rationale for the increased economic wellbeing associated with a Super Bowl victory.

Additionally, we rely on the psychological literature and argue that the economic benefits of a winning team should extend beyond just the championship team to the cities of teams that experience seasonal success. To examine whether a winning effect can be extended to all teams in the league and is not limited to just the Super Bowl champion, we include the winning percentage of the local NFL team. Although lacking a formal model,

ABBREVIATIONS

GMM: Generalized Method of Moments MLB: Major League Baseball NBA: National Basketball Association NFL: National Football League

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the psychological literature suggests multiple individual-level processes that may account for the economic impact of winning percentage. To test whether the effect is based on increased consumption or increased productivity, we estimate our models on the real wage income per capita as well as personal income.

Additionally, because the econometric model is a dynamic panel series model, a model that can exhibit substantial bias in the coefficients (Judson and Owen 1999), we use the method of Arellano and Bond (1991) to correct for bias. This method also provides insight in regard to the directionality of the winning percentage and personal income relationship, specifically that winning percentage drives changes in personal income as opposed to changes in personal income impacting winning percentage. In the Arellano–Bond estimations, winning percentage is treated as endogenous, meaning within the system, while the remaining variables are treated as being exogenous. As an additional further check, we reestimate the model including team salary. If the direction of causation flows from income to winning, it would be indicated by increases in the coefficient on payroll for the team. The results show that even after including team salaries in the model, winning percentage still positively impacts income.

I. PSYCHOLOGICAL IMPACT OF SPORT TEAM'S SUCCESS

Research has consistently demonstrated that people go to great lengths to publicly identify with winning sport teams (Cialdini et al. 1976; Cialdini and Richardson 1980; End 2001; Joinson 2000; Wann and Branscombe 1990). This tendency to bask in the reflected glory (Cialdini et al. 1976) is related to event-specific success (a team's victory) and global success (winning percentage, qualifying for play-offs, etc.). Specifically, End et al. (2002) found that when sport fans were asked to identify their favorite teams, the teams with which they identified had an average winning percentage significantly greater than 50%. Additionally, End et al. (2002) found a positive relationship between the fan preference and their team's winning percentage and between fan preference and team identification. These findings suggest that an individual's preference for a team and one's psychological identification with a sports team are influenced by the team's global (seasonal) performance.

The positive relationship between team performance and identification has a multitude of consequences for sport fans. In comparison to those with low team identification, those fans who have a strong identification with a team or those whose identification with a sports team is strengthened as a result of the team's successes experience stronger emotional reactions in response to their team's victories and defeats (Branscombe and Wann 1992; Wann et al. 1994). Additionally, Wann et al. (1999) reported finding a positive relationship between team identification and psychological health. Individuals who highly identified with a local team reported a healthier mood profile than individuals who reported low levels of identification. Finally, Schwarz et al. (1987) found that citizens of Germany reported higher levels of life satisfaction following a national soccer team's victory than they did prior to the game.

The impact of team performance on the sport fan is not limited to mood. Hirt et al. (1992) found that sport fans' judgments of their personal capabilities are influenced by the performance of the team with which they identify. Specifically, high-identifying fans who witnessed a victory reported higher personal competencies on mental, social, and motor skill tasks than fans who witnessed their sport team being defeated. Highly identified fans also report a decrease in self-esteem following their team's defeat (Bizman and Yinon 2002; Hirt et al. 1992).

If a sport team's performance influences judgments of personal competencies, mood, self-esteem, and so on, one could argue that it is possible that the outcome of a sporting event may influence one's performance at work. Judge and Watanabe (1993) theorize that positive mood experienced in one context (life satisfaction) can "spill over" to other contexts, including one's work environment. Judge and Watanabe argue and provide empirical evidence that this reciprocal spillover effect can account for the strong positive correlation between life satisfaction and job satisfaction (Tait, Padgett, and Baldwin 1989). Because meta-analytical research has demonstrated a positive relationship between job satisfaction and job performance (Iaffaldano and Muchinsky 1985; Judge et al. 2001), the joy experienced by fans of successful teams may spill over and positively influence job satisfaction as well as their performance at work.

One might also argue that post-victory increases in fans' self-esteem and personal competencies indirectly account for improved job performance. As mentioned earlier, Hirt et al. (1992) found that fans who witnessed a victory reported higher personal competency on a variety of tasks. Because the increase in perceived competency was not limited to sports-related tasks, sport fans may experience a spillover and experience increased perceived competency at work as a result of the team's successes. Judge and Bono (2001) conducted a meta-analysis of the research examining the relationship between self-esteem and job performance. The authors found a positive relationship between job performance and self-esteem, which, as mentioned earlier, is also related to a sport team's success. Thus, the spillover of happiness, increased self-esteem, and selfcompetency may account for Lever's (1969) report that the outcome of soccer matches influenced workplace productivity in Brazil. Lever reported that victories were accompanied by increased production, while defeats resulted in an increase in workplace accidents.

Team success can also impact the economy via increased consumption, spending. Isen (1989) demonstrated that positive mood, similar to the mood experienced by fans of successful sport teams, positively impacts the economy via increased consumption. Evidence from the sport fan literature suggests that team success might influence spending. Specifically, research has demonstrated that spontaneous charitable contributions increase following a sport team's successes (Platow et al. 1999).

Although team success might bolster spending, the time of year when each of the leagues' seasons occur may strengthen other seasonal effects on consumption. Whereas the Major League Baseball (MLB) season has ended and the National Basketball Association's (NBA) season is still more than 5 mo from the start of its play-offs, December is the peak of the NFL season (the end of the season and play-offs). Large seasonal effects in output and income are often attributed in part to increased consumer demand as people purchase their holiday gifts and other seasonal items. These seasonality effects can influence business cycles greatly (Beaulieu, MacKie-Mason, and Miron 1992; Cecchetti, Kashyap, and Wilcox 1997; Wen 2002). Therefore, increased consumer spending due to the success of the football team, coupled with the holiday season, could lead to greater economic activity, which is evident in annual data.

The performance of sport teams predicts the extent to which fans identify with the teams. Team performance affects personal reactions and, thus, may have real consequences for the economy. For the reasons stated above, we hypothesize that team's winning performance predicts personal economic wellbeing, specifically demonstrated by increases in real per capita income and real wage income per capita. Because the NFL is the most popular league in the United States and thus the team success would impact the greatest number of fans, we hypothesize that the predicted relationship between winning percentage and economic well-being would be strongest among fans of the NFL.

II. ECONOMETRIC METHOD

We estimate the following dynamic panel model:

(1)
$$y_{it} = \alpha + y_{i,t-1}\gamma + x_{it}\beta_i + \eta_i + \varepsilon_{it},$$

where x_{it} is a series of explanatory variables that are included in the model and y_{it} is the real per capita income for each city *i* in year *t*. η_i is a fixed effect. The cities examined are metropolitan statistical areas as defined by the Bureau of Economic Analysis. The per capita personal income is deflated from nominal to real by using the national consumer price index. Judson and Owen (1999) explain that a fixed-effects model is typically desirable for macroeconomic analysis when the sample includes almost all the entities of interest. The first set of analyses is done on the Coates and Humphreys' (2002) data set. In this study, we are including every American city that had an NBA, MLB, or NFL team in the sample (38 cities) over the time span of 1969–1998. Included in the explanatory variables in the x_{it} vector are the population growth rate, a time trend for each city, and a dummy variable for each year. Also included in the regression are variables reflecting the sports environment: the stadium size, the presence of professional sports teams, as well as the entrance of new teams into the market or the departure of old teams from the market, and years in which the city hosted a Super Bowl. Last, we include Coates and Humphreys'

(2002) "success" variables, i.e., dummy variables for winning championships and making play-offs. All the variables mentioned were included in Coates and Humphreys' (2002) initial analysis. In order to test our hypotheses, the winning percentages of the local sports teams are added to the model. These variables are intended to test further the finding of Coates and Humphreys that a Super Bowl victory has a positive effect on the economic environment, specifically personal income. The winning percentages of the NFL franchises allow us to test whether the effect extends to teams that were successful during the regular season but that were unable to win the Super Bowl. In addition to the Coates and Humphreys' data set, we analyze Matheson's (2005) data set as a robustness check. The Matheson data set includes a larger sample of cities, 73 of the largest cities, and also three additional years of data (1999–2001). Consistent with Matheson's approach of including dummy variables for other major events that impacted local economies, we include dummy variables for the occurrence of Hurricane Andrew, the oil boom and busts in Texas and Louisiana, and the tech boom and bust in San Jose and San Francisco.

Equation (1) can also be estimated using the same explanatory variables as listed above but with the dependent variable (y_{it}) being the real wage income per capita for each city as opposed to the real per capita personal income. Personal income measures income from all sources, including labor and capital. Wage income only includes wages and other forms of monetary compensation to employees. Evidence of an increase in the real wage income per capita could shed light on the way in which sports team success affects personal income. If productivity increases, at least some of the increased business income should flow to the workers in the form of increased wages. Therefore, if we fail to see an increase in the real wage income per capita, it suggests the possibility that workers have not increased their productivity.

The potential problem with relying solely on the above equation is that the coefficients on the explanatory variables are subject to bias due to the presence of the lagged dependent variable. In order to correct for this, we will also estimate the dynamic panel model of Arellano and Bond (1991). This model is a generalized method of moments (GMM) model, which uses the lagged values of the endogenous explanatory variables as instruments. The endogenous variables are the factors that have the potential to be affected by changes in income, as opposed to affecting income. In our model, the endogenous variables are the football winning percentage and football winning percentage squared variables. The model that is estimated is the firstdifferenced version of Equation (1) above:

(2)
$$\Delta y_{it} = \alpha + \Delta y_{i,t-1}\gamma + \Delta x_{it}\beta_i + \Delta w_{it}\xi_i + \varepsilon_{it}.$$

In addition to differencing the equation, which eliminates the bias, the explanatory variables are separated into two groups, x represents the exogenous variables and w represents the endogenous variables. The first thing the differencing accomplishes is to remove the fixed effect from the model (η) but at the same time cause the error term to become correlated with the lagged dependent variable, which can bias the estimate.

In order to solve this problem, an instrumental variable approach is applied. These instruments include the lagged levels of the endogenous variable y, the lagged levels of the endogenous variables w, and the lagged and current values of the exogenous variables x. To address concerns over the endogeneity of the football winning percentage variables, these variables are declared to be endogenous. The remaining explanatory variables are assumed to be exogenous.

Judson and Owen (1999) present various methods that reduce the bias in the estimates and argue that the Arellano–Bond method reduces the bias significantly.²

III. RESULTS

The results of Equation (1), which are presented in Column 1 of Table 1, show that winning percentage of the local professional football team has a positive effect on real per capita income.³ The coefficient for the square of winning percentage is negative;

^{2.} Although Judson and Owen claim that a method that they derive from the work of Kiviet (1995) is slightly superior to the Arellano and Bond method, we used the Arellano and Bond method because of its practicality.

^{3.} The time trend and year dummy variables as well as the sports environment variables for baseball and basketball are suppressed in the tables but included in the regressions.

| | (01011111) 200 | or squares zoun | | |
|-----------------------------------|---------------------------|--------------------------------|---------------------------|--|
| | 1 | 2 | 3 | 4 |
| Explanatory Variables | Real Per Capita Income | Real Wage Income Per Capita | Real Per Capita Income | Growth Rate of Real Per Capita Income |
| Real per capita income (-1) | 0.823** (0.017) | | | |
| Real wage (-1) | | 0.840** (0.015) | | |
| Football franchise | -3.518** (0.955) | -0.232** (0.079) | -3.667* (1.752) | -0.023** (0.007) |
| Football win % | 5.193* (1.998) | 0.334* (0.165) | 2.442 (3.666) | 0.037* (0.015) |
| Football win % squared | -4.083 (2.172) | -0.238 (0.179) | -3.322 (3.987) | -0.028 (0.016) |
| Football stadium capacity | 0.015* (0.023) | 0.002 (0.002) | 0.106* (0.042) | 0.000 (0.000) |
| Football stadium capacity squared | -0.000 (0.000) | -0.000(0.000) | -0.001** (0.000) | 0.000 (0.000) |
| Football stadium construction | -0.042 (0.298) | 0.002 (0.024) | -1.212* (0.545) | 0.002 (0.002) |
| Multipurpose stadium construction | -0.448 (1.535) | -0.046 (0.127) | 7.603** (2.800) | -0.014 (0.011) |
| Football team entry | 0.947* (0.399) | 0.050 (0.033) | 1.876* (0.732) | 0.003 (0.003) |
| Football team departure | -0.960 (0.493) | -0.030 (0.041) | 0.282 (0.904) | -0.008* (0.004) |
| Football team makes play-offs | -0.263 (0.251) | -0.002 (0.021) | -0.246 (0.460) | -0.002(0.003) |
| Football conference championship | 0.055 (0.437) | -0.006 (0.036) | 0.268 (0.803) | -0.001 (0.004) |
| Super Bowl champions | 1.391* (0.589) | 0.089 (0.049) | 1.791 (1.081) | 0.010* (0.003) |
| Host of Super Bowl | -0.131 (0.414) | -0.015 (0.034) | 0.062 (0.761) | -0.001 (0.004) |
| Baseball franchise | 3.296* (1.360) | 0.166 (0.112) | 7.912** (2.490) | 0.014 (0.010) |
| Baseball win % | -0.761 (1.715) | -0.056 (0.141) | -1.375 (3.148) | -0.002 (0.013) |
| Basketball franchise | 0.104 (0.498) | 0.019 (0.041) | 0.352 (0.914) | 0.000 (0.004) |
| Basketball win % | 0.990 (0.858) | 0.072 (0.071) | 1.092 (1.575) | 0.008 (0.006) |
| Population growth | 0.508** (0.092) | 0.066** (0.007) | 1.908** (0.159) | 0.001 (0.001) |
| Constant | 18.532 (1.848) | 1.063** (0.121) | 100.968** (1.226) | 0.006 (0.005) |

 TABLE 1

 Effect of Winning and Football Variables on Income and Wage (Ordinary Least Squares Estimation)

Note: Standard errors in parentheses.

*Significant at the 5% level; **significant at the 1% level.

however, the overall effect of the winning percentage when both variables are included is positive. The overall effect of having a team in a city is unclear because the football franchise indicator variable is negative and significant. Specifically, Table 2 shows the gain in real per capita personal income per win (based on a 16-wk season). There appears to be a nonlinear relationship between winning and income. It is important to note that adding the winning percentage variable does not eliminate the significance of the Super Bowl coefficient originally observed by Coates and Humphreys (2002). Although there are positive economic effects of sharing residency with a team that has been successful over the course of the season (winning percentage), the results suggest that winning the Super Bowl accentuates the effect and delivers a "January bonus." Table 2 also indicates that the positive effect of winning is stronger for the first few wins. We can suggest three explanations for this finding. The first is that the economic benefit may be due to loss avoidance. Alternatively, the real economic benefit may be from having a hometown team in the play-offs, or at least play-off contention (which would be those teams that have managed to win eight or more games). Last, the nonlinearity results may be influenced more strongly by extreme values, of which there are a limited number of observations (e.g., there have been very few teams that have won 1 or fewer or 15 or more games in an NFL season). Also the MLB and NBA variables are not significant, confirming Coates and Humphreys' finding that only the NFL has any effect.

We conduct additional analyses to provide insight into the economic process, specifically increased consumer spending and increased productivity, accounting for the observed effect of success on income. Whereas an increase in real per capita personal income may be the result of increased consumer

| Additional Win during Season | Marginal Increase in Per Capita Personal Income (\$) | | | |
|---------------------------------|---|--|--|--|
| 1 | 30.86 | | | |
| 2 | 27.67 | | | |
| 3 | 24.48 | | | |
| 4 | 21.29 | | | |
| 5 | 18.10 | | | |
| 6 | 14.91 | | | |
| 7 | 11.72 | | | |
| 8 | 8.53 | | | |
| 9 | 5.34 | | | |
| 10 | 2.15 | | | |
| 11 | -1.04 | | | |
| 12 | -4.22 | | | |
| 13 | -7.415 | | | |
| 14 | -10.60 | | | |
| 15 | -13.79 | | | |
| 16 | -16.98 | | | |

 TABLE 2

 Value of Each Win to Personal Income

Notes: The table indicates the increase in per capita personal income of adding one more win by the NFL franchise during the season. For instance, a team winning their seventh game would add an additional \$11.72 over the team only winning six games.

spending, an increase in real per capita wage income may imply an increase of productivity. To examine this alternative source of economic impact, the identical regression analysis presented earlier is conducted including real wage income per capita instead of the real per capita personal income. As shown in Column 2 of Table 1, we find that winning percentage has a significant positive impact on real wage income per capita. This finding supports, albeit indirectly, the idea that the increase in income may be partially due to increased productivity. Interestingly, the Super Bowl championship variable does not show the same significant impact on real per capita wage income. Despite having a positive effect (.081), the effect is not significant (p = .094).

Inclusion of the lagged dependent variable might bias the coefficients. Typically, this bias issue is resolved as the time dimension of the panel moves toward infinity. Although the time frame of our data set is fairly long (30 yr of data), Judson and Owen (1999) suggest that a data set of this length may still be susceptible to bias. This potential bias can be addressed in a variety of ways.

One way of addressing this potential bias is to simply remove the lagged dependent variable from the regression analysis. This method was employed by Coates and Humphreys (2002). To minimize the bias in this investigation, the regression was rerun without the lagged dependent variable. As presented in Column 3 of Table 1, the coefficient associated with football winning percentage is now negative and not significant. A shortcoming with analyzing the data in this manner is that a dynamic aspect to the data is not incorporated into the model when the lagged dependent variable is excluded. Coates and Humphreys (2003) argue that the inclusion of the lagged dependent variable in the model is preferable because it captures other extraneous permanent effects to a city that are not included as explanatory variables. If excluded, these effects could lead to omitted variable bias. Such extraneous events could include public building projects such as transit systems or a convention center, as well as the entry of major private enterprises into the city.

Another solution to the problem of bias is to regress the growth rate of real per capita income on the above variables. Because the growth rate (percentage change) includes information on last year's income, estimating this model does not require the inclusion of the lagged dependent variable. As shown in Column 4 of Table 1, the football winning percentage clearly has a positive effect on the growth rate of real per capita personal income. A finding of a positive effect on the growth rate is not a derivative of the same finding on the level of real per capita personal income. However, since the two results show an increase in income due to an increase in winning percentage, they complement each other and strengthen the argument in favor of successful football teams having a positive effect on the local economy. To further elaborate on the difference between the two analyses, Coates and Humphreys (1999) find that the presence of sports teams has no effect on the growth rate of personal income but did find a negative effect on the level of personal income.

Last, we estimate the model using the Arellano and Bond (1991) GMM procedure. Judson and Owen (1999) show that this method greatly reduces the bias relative to the simple ordinary least squares method of estimation. These results are presented in Table 3, and the coefficients on winning percentage and winning percentage squared are similar in magnitude to their values in Table 1 and still

| | 1 | 2 |
|--|---------------------------|---------------------------------|
| Explanatory Variables | Real Per Capita Income | Real Wage Incomer Per Capita |
| Real per capita income (-1) | 0.804** (0.016) | |
| Real wage income (-1) | | 0.826** (0.013) |
| Football franchise | -3.827** (0.852) | -0.248** (0.064) |
| Football win % | 6.130** (1.823) | 0.408** (0.136) |
| Football win % squared | -5.221** (1.975) | -0.326* (0.148) |
| Football stadium capacity | 0.011 (0.021) | 0.002 (0.002) |
| Football stadium capacity squared | 0.000 (0.000) | 0.000 (0.000) |
| Football stadium construction | 0.033 (0.275) | 0.011 (0.021) |
| Multipurpose stadium construction | -0.292 (1.369) | -0.042 (0.103) |
| Football team entry | 0.871* (0.366) | 0.045 (0.028) |
| Football team departure | -1.130* (0.440) | -0.034 (0.033) |
| Football team makes play-offs | -0.243(0.221) | -0.002 (0.017) |
| Football conference championship | -0.140 (0.382) | 0.004 (0.029) |
| Super Bowl champions | 1.262* (0.515) | 0.078* (0.039) |
| Host of Super Bowl | -0.170 (0.360) | -0.015 (0.027) |
| Baseball franchise | 3.083* (1.253) | 0.184* (0.094) |
| Baseball win % | -1.177 (1.525) | -0.056 (0.114) |
| Basketball franchise | 0.198 (0.452) | 0.009 (0.034) |
| Basketball win % | 1.041 (0.767) | 0.088 (0.057) |
| Population growth | 0.546** (0.083) | 0.066** (0.006) |
| Constant | 0.858 (0.078) | 0.038** (0.004) |
| Statistical test for | | |
| p Value for test of null hypothesis of no autocovariance in residuals of order 1 | .000 | .000 |
| p Value for test of null hypothesis of no autocovariance in residuals of order 2 | .622 | .007 |

 TABLE 3

 Effect of Winning and Football Variables on Income and Wage (Arellano–Bond Estimation)

Note: Standard errors in parentheses.

*Significant at the 5% level; **significant at the 1% level.

significant. The coefficient on the Super Bowl victory variable also exhibits a similar result to the result found in Table 1.

In order for the estimates to be considered consistent, the presence of second-order serial correlation must be ruled out. Presented in Column 1 of Table 3 is the p value of the Arellano–Bond test for second-order serial correlation. The test statistic is miniscule (-.49), and therefore, we conclude that there is no second-order serial correlation in the residuals.

In Column 2 of Table 3, the results of the Arellano–Bond estimation regressing the real wage income per capita instead of the real per capita personal income are presented. Again, the coefficient on the football winning percentage is positive and significant. However, this estimation may not be valid because the assumption of no second-order autocorrelation is rejected.

These results demonstrate that the effect of higher winning percentages for the local NFL team on per capita personal income is quite robust. We are unable to discern whether the observed effect is related to a consumption effect or increased productivity. Our attempts to refute the productivity argument were thwarted when we found that the real wage income per capita also increases in response to increases in winning percentage. In support of the consumption hypothesis, the coefficients on basketball and baseball winning percentages are not significant in any of the estimations. As noted earlier, these two sports are not as popular as the NFL, and their seasons do not intersect with Christmas as directly as football, producing less of an effect under the consumption hypothesis.

IV. ROBUSTNESS CHECKS

Supplemental Data

Column 1 of Table 4 presents the results of Equation (1) using Matheson's (2005) data which include more cities (73) than Coates and Humphreys' data set and three additional years of data (1999–2001). The results parallel those generated from the Coates and Humphreys' data set.

We employ a hybrid of both Coates and Humphreys' (2002) and Matheson's (2006) methodologies. Consistent with Matheson's (2005) critique of Coates and Humphreys' methodology, we include a variable for each team's winning percentage separately. However, unlike Matheson, we do not estimate separate regressions for each city and instead estimate a fixed-effects model across all cities. Our approach does not correct for all of Matheson's criticism (i.e., fixed-effects models being subject to heteroskedasticity); however, it does loosen the requirement that the success of each team be the same across all cities. Although this approach does not eliminate the possibility that one of the multitude of variables would be deemed significant spuriously, the inclusion of each winning percentage variable provides an additional opportunity to critically examine the hypothesized effects. Specifically, if only one winning percentage variable is significant, we can ignore the winning percentage effect. If many winning percentage variables are significant, it suggests that the effect is important across cities. Last, this methodology allows an easy comparison of the effects on income of all the city winning percentages through an F test.

Table 4 presents this regression in Column 2. Although the size of the coefficients varies greatly, four of the coefficients (all positive) are significant at the 5% level. The four cities are Houston, Minneapolis, Oakland, and Orange County, so they are quite diverse cities, and unlikely to be affected by the same unaccounted-for effect. Additionally, the majority of the insignificant coefficients are positive as well. The *F* test suggests that all the football winning percentage parameters together would be significant at the 10% level (F = 1.34, p = .095). Overall, the effect of the winning percentage percentag

centage variables seems to contribute positively toward the income of the area.

Causality

One concern with both the results found here and those reported by Coates and Humphreys (2002) is the direction of causation. We have concluded that a successful sports team strengthens an economy. An alternative explanation is that a successful sports team is a product of increased economic activity.

One argument in favor of causation running from team success to economic output is that the NFL winning percentage is significant, while the MLB one is not. Einolf (2004) showed that payroll was more strongly correlated with team success in MLB than in the NFL and that there seems to be little correlation between market size and payroll in the NFL. Unlike MLB, the NFL has a salary cap. Additionally, the NFL has a greater degree of revenue sharing, an attempt to keep teams equal regardless of their economic situations, than MLB.

Empirical support for the "income affects team success" argument would need to be consistent with the following causal path: higher income creates a greater demand for sports, which results in greater spending by the team, which cumulates in greater team success. Contrary to the income affects success predictions, the league that shows the stronger relationship between success and spending (baseball) does not show the stronger relationship between success and personal income (football).

Attempts were made to statistically test for the endogeneity of the football winning percentage. Specifically, in the Arellano–Bond results in Table 3, the winning percentage variables were included endogenously. The coefficients on the winning percentages were significant in these estimations.

The second statistical method we employ to test for the endogeneity is to include an additional variable in the model to incorporate the effect of income on the success of the team. Table 5 presents the results of the earlier regressions, including a variable for football team salary. Our assumption is that if the income of the city leads to a greater investment in the team, this relationship should be accounted for by the salary variable. If the winning percentage remains significant after

| Real Per Capita Income, NPL Win % Variable Real Per Capita Individual NFL Win % Variable Lagged real PCPI 0.843** (0.011) 0.836** (0.011) Population growth 919.413 (1,568.469) 1,212.793 (1,582.683) Football play-offs 0.42 (25.033) -2.403 (26.263) Olympics 168.866 (241.933) 143.007 (248.642) Oli boom 270.686** (44.120) 267.551** (44.533) Oli boum -160.886* (70.740) -162.670* (71.686) Hurricane Andrew -1,377.835** (28.639) -1,311.152** (239.625) Tech boom 1999 1.982.275** (179.010) 2.069.932*** (188.053) Tech boom 1999 1.982.275*** (179.010) 2.069.932*** (188.053) Tech boom 2000 4,465.379** (181.975) 4,550.926*** (188.053) Tech bout -1.773.961*** (199.346) -1.702.28*** (188.053) Tech bout -2.254 (260.674) Baltimore Boston 20.974 (146.723) Baltimore Boston 20.974 (168.723) Chaleste Denver -31.4904 (221.621) Chaleste Charlotte 177.961** 92.92.460 (250.364) | | 1 | 2 Real Per Capita Income, Individual NFL Win % Variables | |
|--|--------------------|---|--|--|
| Lagged real PCPI 0.843** (0.011) 0.836** (0.011) Population growth 919.413 (1,568.469) 1,212.793 (1,582.683) Football franchise -42.121 (40.861) -110.056 (* (5,180) Football franchise -0.142 (25.033) -2.403 (26.263) Olboom 270.686** (41.120) 267.551** (44.423) Ol bust -160.886* (70.740) -162.670* (71.686) Hurricane Andrew -1,307.835** (238.639) -1,311.152** (239.625) Tech boom 1999 1.982.275** (179.010) 2,069.523** (188.166) Tech boom 1999 1.982.275** (179.010) 2,069.524** (188.165) Tech boom 2000 4.465.379** (181.975) 4.550.926** (188.053) Tech boom 2000 4.465.379** (181.975) 4.550.926** (188.053) Tech boom 2000 4.465.379** (181.975) 4.550.926** (188.053) Batimore 220.974 (168.73) 220.974 (168.73) Batimore 220.974 (168.73) 220.974 (168.73) Batimore 220.974 (168.73) 220.974 (168.73) Batimore 220.974 (168.73) 220.577 Batimore 220.974 (168.73) 220.577 | Variable | Real Per Capita Income, NFL Win % Variable | | |
| Population growth 919.413 (1,568.469) 1,212.793 (1,582.683) Football play-offs 42.121 (40.861) 10.056* (53.180) Football play-offs -0.142 (25.033) 143.097 (248.642) Oll bourn 270.686** (44.120) 267.551** (44.533) Oil bust -160.886* (70.704) -162.670* (71.686) Hurricane Andrew -1,307.835** (238.639) -1,311.152** (239.625) Tech boom 2000 4.465.379** (181.975) 4,550.926** (188.053) Tech bour 2000 4.465.379** (181.975) 4,550.926*** (188.053) Tech bour 2000 4.465.379** (181.975) 4,250.926*** (188.053) Tech bour 2000 4.465.379** (181.975) 4,250.926*** (188.053) Atlanta -2.254 (260.674) 28.077) Atlanta -1.702.83*** (200.414) 210.974 (168.723) Batimore 220.974 (168.723) 224.60 (250.877) Charlott -1.702.80 (255.891) 20.974 (168.723) Batimore 220.974 (168.723) 22.555) Charlot -70.250 (255.891) 20.860 (250.781) Datason 34.045 (211.72) 20.860 (250.781) <td>Lagged real PCPI</td> <td>0.843** (0.011)</td> <td>0.836** (0.011)</td> | Lagged real PCPI | 0.843** (0.011) | 0.836** (0.011) | |
| Football franchise 42.12 (40.861) 110.058* (53.180) Football play-offs -0.142 (25.033) -2.403 (26.263) Oll boom 270.686** (44.120) 267.551*** (44.533) Oil boam -160.676* (54.1433) -111.152*** (239.625) Tech boom 1999 1.982.275*** (179.010) 2.069.523*** (188.053) Tech boom 2000 4.465.379*** (181.975) 4.550.926*** (188.053) Tech boom 2000 4.465.379*** (199.346) -1.702.283** (200.414) FB win % 120.978* (60.519) -2.254 (260.674) Atlanta -2.254 (260.674) Baltimore Baltimore 220.974 (166.723) Boston 34.043 (211.472) Baltimore 220.974 (166.723) Botton 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -71.47.484 (276.674) Defroit -70.250 (235.85) Cleveland -66.401 (228.433) Dallas 292.460 (250.344) Derver -24.157 (260.184) Dertoit 91.669 (276.722) </td <td>Population growth</td> <td>919.413 (1,568.469)</td> <td>1,212.793 (1,582.683)</td> | Population growth | 919.413 (1,568.469) | 1,212.793 (1,582.683) | |
| Football play-offs -0.142 (25.033) -2.403 (26.263) Olympics 168.866 (241.933) 141.097 (248.642) Oil boom 270.686** (44.120) 267.551** (44.533) Oil bust -160.886* (70.740) -162.670* (71.686) Hurricane Andrew -1,307.835** (238.639) -1,111.52** (239.625) Tech boom 1999 1,982.275** (179.10) 2,069.523** (188.146) Tech boom 2000 4,465.379** (181.975) 4,550.926** (188.053) Tech bots -1,773.961** (199.346) -1,722.83** (200.414) PB win % 120.978* (60.519) 200.974 (168.723) Matata -2.254 (260.674) 200.974 (168.723) Boston 34.043 (21.1472) 201.974 (168.723) Bottata -2.02.974 (168.723) 202.460 (21.621) Chriatote -314.904 (21.621) 21.620 (21.621) Chriato -34.943 (22.162) 21.620 (25.378) Chriato -314.904 (21.621) 21.620 (25.378) Dallas 292.460 (25.378) 22.9450 (25.378) Darkor -241.577 (260.184) 21.669 (27.6722) Houston <td< td=""><td>Football franchise</td><td>-42.121 (40.861)</td><td>-110.056* (53.180)</td></td<> | Football franchise | -42.121 (40.861) | -110.056* (53.180) | |
| Olympics 168.866 (241.933) 143.097 (248.642) Oil boom 270.686** (44.120) 267.551** (44.533) Oil bust -160.886* (70.740) -162.670* (71.686) Hurricane Andrew -1.307.835** (238.639) -1.311.152** (239.625) Tech boom 1999 1,982.275** (179.010) 2.069.523** (188.053) Tech boom 2000 4.465.379** (181.975) 4.550.926** (188.053) Tech boust -1,773.961** (199.346) -1,702.283** (200.414) FB win % 120.978* (60.519) -2.254 (260.674) Atlanta -2.254 (260.674) 83.859 Batimore 220.974 (168.723) 83.57 Boston 34.043 (211.472) 83.59 Buffalo 38.359 (205.877) Charlotte Charlotte 417.486 (277.863) Chicago Charlotte 417.486 (277.863) Chicago Denver -244.07 (201.814) 202.460 (203.364) Denver -244.07 (201.814) 201.614) Detroit 91.669 (277.22) Houston 425.571* (173.961) Indianapolis 519.919* (260.367) <td< td=""><td>Football play-offs</td><td>-0.142 (25.033)</td><td>-2.403 (26.263)</td></td<> | Football play-offs | -0.142 (25.033) | -2.403 (26.263) | |
| Oil boom 270.686** (44.120) 267.551** (44.533) Oil bust -160.868* (70.740) -16.670* (71.686) Hurricane Andrew -1.307.835** (238.639) -1.311.152** (239.625) Tech boom 2000 4.465.379** (181.975) 4.550.926** (188.053) Tech bust -1.773.961** (199.346) -1.702.283** (200.414) FB win % 120.978* (60.519) -2.254 (260.674) Baltimore 220.974 (168.723) Boston Baltimore 220.974 (168.723) Boston Charlotte 417.486 (277.863) Charlotte Charlotte 417.486 (277.863) Charlotte Charlotte -54.01 (228.433) Dallas 292.460 (250.364) Denver -24.1577 (260.184) Denver 91.669 (257.781) Detroit 91.669 (257.781) Jacksonville 106.049 (251.707) Kanasa City -81.205 (257.571) Ida.8389 Ida.8389 Jacksonville 10.6049 (237.407) Kanasa (237.407) Kanasa City -81.205 (257.571) Ida.8338) Miami 292.0749 (343.338) Mineapolis | Olympics | 168.866 (241.933) | 143.097 (248.642) | |
| Oil bust -160.886* (70.740) -162.670* (71.686) Hurricane Andrew -1,307.835** (238.639) -1,311.152** (239.625) Tech boom 1999 1,982.275** (179.010) 2,2695.235** (188.46) Tech boom 2000 4,465.379** (181.975) 4,550.926** (188.053) Tech bust -1,773.961** (199.346) -1,702.283** (200.414) FB win % 120.978* (60.519) -2.254 (260.674) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.589 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (230.364) Denver -241.577 (260.184) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Mianei 220.0749 (343.338) Mianei | Oil boom | 270.686** (44.120) | 267.551** (44.533) | |
| Hurricane Andrew -1,307.835** (238.639) -1,311.152** (239.625) Tech boom 1999 1,982.275** (179.010) 2,069.525** (188.053) Tech bous -1,773.961** (199.346) -1,702.283** (200.414) FB win % 120.978* (60.519) -2.254 (260.674) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffinore 220.974 (168.723) Charlotte 417.486 (277.863) Charlotte 417.486 (277.863) Cheago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -92.640 (250.364) Denver -241.577 (260.184) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 81.345 (238.800) New Orleans | Oil bust | -160.886* (70.740) | -162.670* (71.686) | |
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| Tech boom 2000 4,465.379** (181.975) 4,550.926** (188.053) Tech bust -1,773.961** (199.346) -1,702.283** (200.414) FB win % 120.978* (60.519) 220.974 (168.723) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.50) Los Angeles 59.305 (189.162) Miami 220.749 (343.338) Minneapolis 519.919* (260.367) New York 2.293 (302.115) Oakland 56.809** (161.083) Orange County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (37.5215) Sat 106.807 (253.72) Sat 106.807 (253.72) San Diego -385.905 (245 | Tech boom 1999 | 1,982.275** (179.010) | 2,069.523** (188.146) | |
| Tech bust -1,773.961** (199.346) -1,702.283** (200.414) FB win % 120.978* (60.519) Atlanta -2.254 (260.674) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -24.1577 (260.184) Denver -24.1577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.50) Los Angeles 59.305 (189.162) Miami 220.740 (34.33) Mianeapolis 51.9.919* (260.367) Nashville 81.345 (238.800) New York 2.233 (302.15) Oakland 586.909** (161.083) Orange County 484.604** (183.241) Philadelphia -9.422.077 (375.215) | Tech boom 2000 | 4,465.379** (181.975) | 4,550.926** (188.053) | |
| FB win % 120.978* (60.519) Atlanta -2.254 (260.674) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (21.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (28.433) Denver -241.577 (260.184) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.945 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.38) Minneapolis 51.9919* (260.367) Nashville 81.345 (238.800) New York 2.293 (302.115) Oakland 56.909** (161.083) Orange County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) San Francisco 368.358 (213.666) San Francisco | Tech bust | -1,773.961** (199.346) | -1,702.283** (200.414) | |
| Atlanta -2.254 (260.674) Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.38) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.22) New Orleans 106.807 (253.323) New York 2.293 (302.115) Okland 586.909** (161.083) Orleange County 484.604*** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) San Francisco | FB win % | 120.978* (60.519) | | |
| Baltimore 220.974 (168.723) Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cinicanati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.406 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.50) Los Angeles 59.305 (189.162) Miami 220.749 (343.38) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New York 2.233 (302.115) Ockland 586.909** (161.083) Orage County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) Photenix -342.077 (375.215) San Francisco 368.358 (216.663) San Francisco 368.358 (216.663) Sholego | Atlanta | | -2.254 (260.674) | |
| Boston 34.043 (211.472) Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.338) Mineapolis 519.919* (260.867) New Orleans 106.807 (253.323) New Orleans 106.807 (253.323) New York 2.293 (302.115) Oatland 90.738 (265.683) Phoenix -342.077 (375.215) Phitabelphia 90.738 (265.683) Phoenix -342.077 (375.215) Phitabelphia 90.738 (265.67) San Francisco 368.582 (213.666) SantF | Baltimore | | 220.974 (168.723) | |
| Buffalo 83.859 (205.877) Charlotte 417.486 (277.863) Chicago -314.904 (21.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.338) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.23) New Orleans 106.6807 (253.23) New Orleans 106.807 (253.23) New Orleans 106.807 (253.23) New Orleans 106.807 (253.23) New Orleans 90.738 (265.683) Phoenix -342.077 (375.215) Philadelphia 90.738 (265.683) Phoenix -385.905 (245.719) San Francisco 368.358 (213.666) Sartle | Boston | | 34.043 (211.472) | |
| Charlotte 417.486 (277.863) Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonvile 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Mianai 220.749 (343.38) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.323) New York 2.293 (302.115) Oakland 586.909** (161.083) Orage County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) San Diego -97.842 (240.993) San Trancisco 368.358 (213.666) Seattle -97.842 (240.993) St. Louis 175.456 (176.537) Tampa 23.011 (278.918) Washington, DC< | Buffalo | | 83.859 (205.877) | |
| Chicago -314.904 (221.621) Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City 81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.338) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.323) New Orleans 106.807 (253.323) Oakland 586.909** (161.083) Orange County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) Pittsburgh 384.843 (285.172) San Francisco 368.358 (213.666) Seattle -97.842 (240.993) St. Louis 175.456 (176.537) Tampa 293.011 (278.918) Washington, DC 241.064 (239.687) | Charlotte | | 417.486 (277.863) | |
| Cincinnati -70.250 (235.895) Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.38) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.323) New York 2.293 (302.115) Oakland 586.909** (161.083) Orange County 484.604** (183.241) Philadelphia 90.738 (256.683) Phoenix -342.077 (375.215) San Diego -385.905 (245.719) San Francisco 368.358 (213.666) Seattle -97.842 (240.993) St. Louis 175.456 (176.537) Tampa 293.011 (278.918) Washington, DC 241.054 (235.578) Constant 3,135.14** (235.578) | Chicago | | -314.904 (221.621) | |
| Cleveland -56.401 (228.433) Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City 81.205 (259.550) Los Angeles 59.305 (189.162) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.323) New York 2.293 (302.115) Oakland 586.909*** (161.083) Orange County 484.604** (183.241) Philedphia 90.738 (256.683) Phoenix -342.077 (375.215) Stan Diego -385.905 (245.719) San Francisco 368.358 (213.666) Seattle -97.842 (240.993) St. Louis 175.456 (176.537) Tampa 293.011 (278.918) Washington, DC 241.064 (239.687) Constant 3,135.14** (235.578) 3,255.587** (237.557) | Cincinnati | | -70.250 (235.895) | |
| Dallas 292.460 (250.364) Denver -241.577 (260.184) Detroit 91.669 (276.722) Houston 425.571* (173.961) Indianapolis 81.560 (255.781) Jacksonville 160.495 (237.407) Kansas City -81.205 (259.550) Los Angeles 59.305 (189.162) Miami 220.749 (343.338) Minneapolis 519.919* (260.367) Nashville 81.345 (238.800) New Orleans 106.807 (253.323) New York 2.293 (302.115) Oakland 586.099** (161.083) Orange County 484.604** (183.241) Philadelphia 90.738 (265.683) Phoenix -342.077 (375.215) Pittsburgh 384.843 (285.172) San Diego -385.905 (245.719) San Francisco 368.358 (213.666) Settle -97.842 (240.993) St. Louis 17.5456 (176.537) Tampa 293.011 (278.918) Washington, DC 241.064 (239.687) Constant 3,135.14** (235.578) 3,255.587** (237.557) | Cleveland | | -56.401 (228.433) | |
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TABLE 4Results Using Matheson Data Set

Note: Standard errors in parentheses. PCPI, per capita personal income. *Significant at the 5% level; **significant at the 1% level.

TABLE 5Results Including Football Salary Variable

| | 3 | | | |
|-----------------------------------|--------------------------------|--------------------------------|---|--------------------------------|
| Explanatory Variables | 1 Real Per Capita Income | 2 Real Per Capita Income | Growth Rate of Real Per Capita Income | 4 Real Per Capita Income |
| Real per capita income (-1) | 0.747** (0.025) | 0.748** (0.025) | | 0.695** (0.023) |
| Football franchise | -3.468* (1.463) | -2.912* (1.293) | -0.011 (0.010) | -2.009 (1.236) |
| Football win % | 3.830 (2.567) | 3.844 (2.567) | 0.033 (0.018) | 1.073 (0.684) |
| Football win % squared | -2.928 (2.797) | -2.889 (2.797) | -0.026 (0.020) | |
| Football salary | 0.000 (0.000) | | -0.000(0.000) | 0.000 (0.000) |
| Football stadium capacity | -0.031 (0.040) | -0.036 (0.039) | -0.000(0.000) | -0.067(0.038) |
| Football stadium capacity squared | 0.001 (0.000) | 0.001 (0.000) | 0.000 (0.000) | 0.001* (0.000) |
| Football stadium construction | -0.533(0.479) | -0.490(0.476) | 0.001 (0.003) | -0.643(0.480) |
| Multipurpose stadium construction | -2.977 (2.287) | -2.745 (2.269) | -0.020 (0.016) | -1.825 (2.271) |
| Football team entry | 1.985** (0.743) | 1.926** (0.739) | 0.011* (0.005) | 2.221** (0.757) |
| Football team departure | -1.415 (0.734) | -1.335 (0.727) | -0.006 (0.005) | -1.873* (0.731) |
| Football team makes play-offs | -0.675* (0.300) | -0.679* (0.300) | -0.004* (0.002) | -0.770** (0.271) |
| Football conference championship | -0.069 (0.554) | -0.068 (0.554) | -0.001 (0.004) | -0.305 (0.526) |
| Super Bowl champions | 0.895 (0.781) | 0.922 (0.780) | 0.007 (0.006) | 0.720 (0.740) |
| Host of Super Bowl | -1.180* (0.518) | -1.166* (0.518) | -0.008* (0.004) | -0.747(0.480) |
| Baseball franchise | -1.430 (0.942) | -1.353 (2.343) | -0.017 (0.017) | -1.154 (2.406) |
| Baseball win % | -2.173 (2.152) | -2.244 (2.150) | -0.007 (0.015) | -0.670 (2.103) |
| Basketball franchise | -0.236 (0.000) | -0.183 (0.941) | -0.003 (0.007) | -0.235 (0.875) |
| Basketball win % | -1.390 (1.183) | -1.407 (1.192) | -0.005 (0.009) | -1.665 (1.139) |
| Population growth | 0.898** (0.134) | 0.899** (0.134) | 0.002* (0.001) | 0.967** (0.125) |
| Constant | 21.699** (3.012) | 20.772 (2.787) | -0.031** (0.011) | 1.159** (0.144) |

Notes: Standard errors in parentheses. Columns 1-3 present results of standard regression. Column 4 presents the Arellano-Bond results.

*Significant at the 5% level; **significant at the 1% level.

the inclusion of the salary variable, it can be interpreted as additional support for the direction of causation originating from winning and thus impacting income. One limitation of this approach of testing endogeneity is that there are a limited number of years of data available (1981–1998).

Column 1 of Table 5 re-creates Column 1 of Table 1 but now includes the football salary variable. The dependent variable is the level of personal income. The salary variable appears to contribute very little to explaining the variation in income. The football winning percentage variables are not as significant and are smaller in magnitude, but that could be expected as the results are based on fewer observations (which reduces statistical power). Column 2 of Table 5 presents the results of the same regression analysis except that, this time, the football salary variable is excluded. The coefficients on football winning percentage and football winning percentage squared are essentially the same regardless of whether the football salaries are included or not. Therefore, we can conclude that winning percentage is affecting income separate from salary.

Presented in Column 3 of Table 5 are the results adjusting the estimation in Column 4 of Table 1 to include the salary of the teams. The impacts of the winning percentage variables, though no longer significant at the 5% level, maintain essentially the same magnitude as they did in Table 1. Also, the coefficients on winning percentage are unaffected by the inclusion of the salary variable.

Column 4 presents the results using the Arellano–Bond methodology, which is a reestimation of Column 1 of Table 3. The winning percentage squared is removed from the equation because it has a very low p value in these estimations. Because we are now explicitly accounting for potential endogeneity of the winning percentage in the model, we assume that the variables are not endogenous. As in

the simple regression results of Column 1 of Table 5, the results on winning percentage are weakened when estimated over the complete sample (1969–1998), but again the salary variable appears to be completely unimportant. The results with football salary excluded over the 1980–1998 time period are not included in the table, but the coefficients on winning percentage in each of these estimations is essentially the same whether salary is included or not.

Overall, the football salary variable has very little influence on the football winning percentage variable. The variable, included to control for more revenues influencing the success of the team, is unable to fully remove the importance of winning on income, which implies that the direction of causation runs from winning to personal income and not vice versa.

V. CONCLUSIONS

Our results extend the work of Coates and Humphreys (2002) by showing that an increase in the winning percentage of the local NFL franchise increases the real per capita personal income of the city. Consistent with this finding, the data suggest that the winning percentage increases the growth rate of real per capita personal income as well. One possible explanation for this relationship is that workplace productivity increases as a function of the team success. The observed increase in the real wage income per capita as a function of team winning percentage, as well as the reviewed literature that demonstrates the psychological impact of team successes, supports this enhanced productivity explanation. The findings seem to be quite robust with regard to estimation methodology, although the regression on real wage income per capita is not as convincing as the regression on per capita personal income.

The nonlinear aspect of the winning percentage results suggests that the gain to personal income from winning is strongest when the team has few wins. There even seems to be a decline in personal income from winning additional games above 11. These results suggest that competitive balance, where the teams perform at a fairly equal level, would benefit the cities. The parity that currently exists in the NFL, and sometimes condemned as mediocrity, is actually good for the economics of the cities that host NFL franchises. These findings suggest that cities should encourage the NFL to incorporate policies to maintain competitive balance.

One recommendation of a concrete policy proposal that can be derived from these results is that cities might want to consider making the contribution toward stadium financing dependent upon the success of the team. Because the benefits that the city derives from the team are higher with a more successful team, the city might want to require that the team makes all efforts to provide a successful team in order to allow the citizens to fully obtain the funding benefits. However, our findings do not show that the success of teams justifies spending money on a stadium in general, supporting the extensive literature that states that the gains from stadium financing to cities are minimal (Baade and Matheson 2004; Baade and Sanderson 1997; Coates and Humphreys 1999, 2003; Noll and Zimbalist, 1997a, 1997b; for an alternative view, see Carlino and Coulson 2004).

Because the nature of the data does not allow for definitive conclusions in regard to the factors that account for the increase in income, economists and psychologists should collaborate to establish a formal model to determine if the increases in real per capita personal income are a result of increases in productivity, consumption, or both factors. The establishment of a formal psychological model may also provide insight into the duration of the observed effects, as well as identify other individual-level factors that may be affected by team performance.

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