Emotions and the Sex Market; Evidence from Market Transactions and Football Matches*

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Abstract

We study the impact of professional football match results on transactions and spending in the commercial sex market. Relying on betting odds, our analysis allows us to decompose this effect into two components: the pure game effect and the emotional channel due to unexpected outcomes. Our findings indicate that unexpected losses of the home team lead to an increase in sex work activity on the day of the match, while expenditures and durations decrease also on the following days. Taken together, our results suggest that the emotional channel dominates the pure game effect.

Keywords: sex work, prostitution, emotions, football games, staggered event study.

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1 Introduction

This paper empirically studies the drivers of paid sexual exchanges, with a focus on the role of emotional shocks. Estimates suggest that the commercial sex industry generates billions of dollars annually, though precise figures are difficult to obtain due to its often unregulated and underground nature in many countries.[1] Although figures related to the sex market are difficult to obtain due to low response rates, stigmatization, and criminalization of the industry (Edlund and Korn, 2002; Gertler et al., 2005; Immordino and Russo, 2015; Bisschop et al., 2017; Cunningham and Shah, 2018; Cameron et al., 2021), there are an estimated 50 million sex workers active worldwide. In the UK, more than 70 thousand workers are estimated to be active in the sex market (International Union of Sex Workers, 2025). In the U.K., the Office for National Statistics estimated that prostitution accounted for nearly 0.3% of GDP.

Beyond the economic figures, paid sex implies several potential implications ranging from individual rights to public health

Using a unique dataset covering sexual transactions in England and Scotland from 2008 to 2019, we analyze detailed information on the types of sexual services offered, pricing, locations, durations, and demographic characteristics of the sex workers.

Emotions and visceral states are powerful drivers of individuals' well-being and behavior in several domains, ranging from intertemporal choice (Elster, 1998; Loewenstein, 2000; Bernheim and Rangel, 2004; Fudenberg and Levine, 2006; Camerer et al., 2005; Pennesi, 2021) to labor supply and productivity (Bellet et al., 2024), from bargaining (Güth et al., 1982; Henrich et al., 2004) to violent behavior (Card and Dahl, 2011; Bindler et al., 2020) and sexual desires (Ariely and Loewenstein, 2006). To assess the impact of emotional shocks, we focus on the outcomes of Premier League football matches.[2]

Based on a difference-in-differences technique, we find that unexpected outcomes in football matches increase the number of transactions. This result is driven by unexpected

[1]A notable exception is Germany, where sex work is legal and regulated since 2002. In 2014, it was estimated that the sex industry generated more than 20 billion euros (https://www.thenewsminute.com/features/prostitution-germany-21-billion-year-industry-26520). Since 2014, the European national accounts must also include estimates of the shadow economy, including prostitution. The industry size varies across countries. It was less than 0.1% of GDP in Sweden (2006), the Netherlands (2008), and Denmark (2004), and slightly over 0.2% in Italy (2011) and Luxembourg (2013). Spain and Portugal are somehow below 0.5% of GDP (International Monetary Found, 2025).

[2]We refer to football as the sport played with a round ball, also known as soccer in the USA and Canada.

losses of the home team, which temporarily increase the number of paid sexual exchanges. On average, however, expenditure and duration of such transactions decreases.

These results are consistent with the notion that emotions are powerful drivers of demand for paid sex. The demand for sex could be a cognitive response to the need of coping with negative emotions due to the unexpected loss.

If this is the case, our findings could be interpreted as evidence of self-medication behavior, consistent with existing research on consumption as a coping mechanism for discomfort, stress, and adverse life situations. Additionally, our results align with the notion that demand for paid sex may also serve as a means to celebrate an unexpected win by supporters of the host team. In either scenario, the observed increase in sex transactions may also be partly attributable to income effects, as unexpected outcomes offer bettors opportunities for unanticipated financial gains.

This paper is connected to different strands of the literature. On the one hand, it is linked to the economic literature studying the determinants of sex work. This branch of the literature studies both the determinants of prostitution as well as the unintended effects of different regulations (see, inter alia, (Edlund and Korn, 2002; Della Giusta et al., 2008; Cunningham and Shah, 2018; Bisschop et al., 2017; Ciacci and Sviatschi, 2021)). Our findings suggest that negative emotions affect equilibrium quantity on the day of the football match. Insofar as the regulation on commercial sex affects customers' behavior, our results might depend on the existing regulation.

On the other hand, our study is connected to the economic literature studying the effect of sports events on crime. Card and Dahl (2011) pioneered research on this topic, they find that football matches trigger intra-partner-violence in the U.S. By the same token, Ivandić et al. (2024) establishes that a similar mechanism is at play in the UK but is connected to football matches. These authors also find that alcohol consumption is a driver of such findings (Bindler et al., 2020). Our paper extends this strand of the literature to commercial sex outcomes. (Andres et al., 2023) study instead the driver fo hooliganism-type of crime triggered by UK football matches, finding that is driven mainly a specific type of culture of respect and honor between fans rather than by the outcome, whether it is disappointing or not, of the games. This provides further motivation for our study since it casts doubt on the mechanism of (Card and Dahl, 2011) which negative outcomes drive fans' violence. We contribute by shedding light on the validity of this mechanism for sex, which has been largely found to be a substitute for violence.

2 Data

This section describes the data used in the article. This article merges a dataset with information on sex worker transactions and a dataset on football matches and betting odds.

2.1 Sex Work in the UK

We rely on a unique and novel dataset collected from two online marketplaces by Peter Backus in Backus and Nguyen (2021). Such a database gathers information on reviewed sexual services at the daily level, taking into account an *id* number for each sex worker, as well as demographic and geographic features. Our sample ranges from year 2008 to 2019 since they are the years covered by this dataset.

Namely, data have been collected from two online sex work platforms. Following Backus and Nguyen (2021) terminology we refer to them as Platform 1 and Platform 2, the largest in Great Britain and Ireland respectively, as of early 2019. Both platforms overlap in Northern Ireland and are freely accessible without registration. In the two platforms, customers are allowed to post reviews on commercial sex transactions after such transactions took place. Thus, information about customers comes from such reviews.

This database includes anonymous information of both service providers and clients, encompassing demographic details (e.g., sex, ethnicity, age), service types (i.e. incall or outcall), pricing in pounds, duration in minutes, and geographical locations given by UK counties. We have 39,246 long-form reviews for the UK and 159 from Northern Ireland (2008-2019). Not all transactions are reviewed, so changes in review numbers may reflect changes in the number of transactions or review likelihood. The combined data includes 32,307 reviews for 4,534 sex workers and 12,053 clients between 2008 and 2019, aggregated into a NUTS2 regional panel. Further information on this dataset is available in Backus and Nguyen (2021).

To carry out the analysis expounded in this paper, we collapse data by county and day. Precisely, we add up the number of transactions and compute the average price and duration for sex records between 2008 and 2019. We compute the ratio between prices and duration to obtain a relative measure of the services provided, from the supply side, and a relative measure of prices, on the demand side. We refer to such a measure as "ratio". We do not have information on the services per se, yet we use the ratio as its proxy.

Moreover, we classify sex workers in "movers" and "stayers". Our classification follows the following criteria: the place where a certain sex workers holds the highest number of transactions in the dataset is considered as their base. Then, any transaction taking place there is considered as a "stayer" transaction, any transaction occurring elsewhere is considered as a "mover " transaction.[3] We rely on this categorization since we do not know directly from the dataset where the sex worker is based. Accordingly, a "mover" is a sex worker who works in a different county from its most common one. A "stayer" is instead a sex worker who works in its most common county.

We also differentiate between in-call and out-call sex workers, this distinction is given in the dataset. An in-call transaction is a transaction that takes place at the sex worker's place. An out-call is a transaction that occurs at the customer's location. Information on in-call and out-call are directly available in the afore-mentioned dataset. It is worth to highlight that this information is not related to "movers" and "stayers". A transaction could take place in the county where the sex workers holds the vast majority of their transactions but at the place of the customer. To put it differently, "movers" and "stayers" refer to whether sex workers move across UK counties, in-call and out-call refers to whether the transaction happens at the place of the sex workers or at the place of the client. Table **??** displays summary statistics from the sex workers dataset. The average age of a sex worker in our sample is around 37 years. The average duration of a transaction is around 1 hour and a half. On average 83% of transactions are incall. Figure 1 shows the distribution of sex work transactions across England and Scotland. We can observe that counties highly populated exhibit more transactions. Figure 2a show the difference between the hourly wage of sex workers using our dataset with respect to the average hourly wage for female individuals in the UK. This difference between the two motivated the first economic papers dealing with prostitution. Such papers used different

[3]In other words, we compute the mode of the place of the transaction across the whole period for each sex worker and set that very place as where the sex worker is based. Consequently, any other place where the transaction happens is a move.

explanations ranging from foregone marriage opportunities to reputation to explain the wage premium displayed in Figure 2a (Edlund and Korn, 2002; Gertler et al., 2005; Della Giusta et al., 2008; Immordino and Russo, 2015). Figure 3a displays sex workers' earnings by ethnicity. Arabic, Asian and Latin American sex workers have the highest earnings. White sex workers' earnings are lower in point estimate but more precise. Figure 3b shows the negative correlation present between sex workers' earnings and age. Note that breaking data at 40 years old could produce a negative slope but flatter. This might be due to mere juvenile traits or marriage and fertility issues (Arunachalam and Shah, 2008).

2.2 Football Matches and Betting Odds

The dataset on English Premier League (hereafter, EPL) and Scottish Premiership (hereafter, SP) football matches is drawn from the website football-data.co.uk. We collect information on the universe of matches taking place in both the EPL and the SP from the 2008/09 season to the 2018/2019 season, for a total of 7,296 games.

By collecting information on betting odds we can also classify matches according to their (un)expected results. Namely, we focus on the bookmaker market before the match. In such a market, bookmakers act as dealers and provide odds against which bettors can place bets. In this framework, we can interpret the reciprocal of odds as an estimate of the probability of certain results (Meier et al., 2021). Thereupon, we can calculate the ex-ante probability of each game following previous literature (Deutscher et al., 2018; Ötting et al., 2023).[4] Next, using the betting odds from one of the most popular sports betting portals, that is, Bet365, we can categorize matches results as expected or unexpected. This approach is similar to (Ivandić et al., 2024).

In this article we focus only on the results of the home team. An expected win (loss) occurs if the home team wins (losses) and its winning probability at the kick-off is lower (higher) than the winning probability of the away team. When we refer to expected and unexpected results, we encompass either both expected victories and defeats or unexpected victories and defeats.[5]

In Table 2 we report the descriptive statistics for both the betting odds and the

[4]The probability of a home team victory is calculated as: $P_h = \frac{1/O_h}{1/O_h+1/O_d+1/O_a}$

[5]We focus on unexpected wins or losses of the home team, discarding draws, from the mechanism analysis to explore the effect of emotions.

calculated implied probabilities. Two features are worth mentioning. First, as expected, winning at home is more likely, so the odds of winning at home are lower and the probability of that same event is higher in point estimate. Second, even if the odds of an away win seems considerably larger than those of a home win, the implied probability does not differ much.

Figure 4 shows the distribution of matches depending on the final result and betting odds. Accordingly, we can first separate matches in defeats, victories and draws, and then in unexpected results and expected results. These two categories might be further separated into unexpected losses and unexpected wins. In this case unexpected draws might be computed subtracting (un)expected defeats and victories from (un)expected results.

Figure 4 shows that home victories are more frequent than home defeats. Second, expected results are three times more frequent than unexpected results. This proportion is even higher when comparing expected wins to unexpected wins. The number of unexpected and expected defeats is similar.

3 A model of sex, emotions and windfall gains

This section presents a model to study how unexpected shocks affecting emotions and income influence both the extensive and intensive margins of the demand for paid sex.

3.1 Demand for paid sex

In a given day, an individual can purchase sex services s at price p and a composite q of non-sex related goods (e.g., food, drinks, clothes). The composite good is taken as the numeraire. The individual utility function $U(s, q)$ is assumed to be strictly concave and strictly increasing in the composite q. We make no assumptions about the marginal utility of paid sex, as individuals may find it pleasurable, unpleasurable, or indifferent.[6]

Given available income M, and conditional on consuming sex, the optimal consumption bundle (s^*, q^*) is given by the familiar first-order condition (subscripts denote partial

[6] In the empirical application, purchased sex is categorized by the type of service and its duration. Let $s = \theta \cdot t$, where θ represents the quality of the service and t its duration. An increase in the amount of consumed sex s can reflect either a longer duration or an improvement in the quality of purchased sex.

derivatives):

$$\frac{U_s(s^*, q^*)}{U_q(s^*, q^*)} = p \tag{1}$$

together with the budget constraint $M = q + ps$. A necessary condition for the equality to hold is that the marginal utility of sex is non-negative. For later reference, denote as s_M the change in the optimal demand of sex when income increases.[7]

Let the indirect utility obtained from consuming the optimal amount of sex be $U(s^*, q^*)$ and denote with σ the stigma cost for consuming sex. It describes a participation cost for engaging in sexual exchanges, which may stem from personal discomfort with paid sex or from social norms and peer pressure that stigmatize being a buyer of paid sex (Della Giusta et al., 2008, 2009; Kotsadam and Jakobsson, 2014). The term σ may alternatively represent the time or transportation fixed cost—measured in utils—incurred when buying sex. Note that it is a fixed, one-off cost that does not vary with the amount of sex purchased. The indirect utility associated to the outside option of not engaging in any sex is $U(0, M)$. If

$$U(s^*, q^*) - \sigma > U(0, M) \tag{2}$$

the individual becomes a buyer of sex, with the amount s^* determined by condition (1) and the budget constraint. Otherwise, they abstain and allocate all their budget to non-sex-related goods.

3.2 Football matches, emotions and windfall gains

In this Section we study how an unexpected outcome in a football match affects the intensive and extensive margin of the demand for sex. We consider two main possible drivers: the role of emotions and of windfall gains from betting.

Regarding the former, based on the empirical evidence we posit that football supporters experience intense emotions about match outcomes, with stronger emotions triggered by more unexpected outcomes. Let $\mu_\varepsilon \geq 0$ represent the effect of an unexpected football match outcome ε on emotions μ. We assume that the emotional arousal described by μ influences both the utility function, $U = U(s, q; \mu)$, and the stigma cost of consuming

[7] Since $s_M = \alpha(U_{qs} - pU_{qq})$, where $\alpha = -\left(p^2 U_{qq} - 2pU_{sq} + U_{ss}\right) > 0$ by concavity of the utility function, sex is a normal good if $U_{qs} > pU_{qq}$ and an inferior good otherwise.

paid sex, $\sigma = \sigma(\mu)$.

For the latter driver, we consider that betting on sports outcomes is common in the UK. Unexpected outcomes can lead to windfall gains for bettors, therefore affecting their available income M—conditional on being a bettor. Denote with $M_\varepsilon \geq 0$ the increase in income due to winning a bet on an unexpected football match outcome. Applying the implicit function theorem, the following holds:

Proposition 1 (Intensive margin) *Conditional on buying sex, an individual buys more sex after an unexpected football outcome if*

$$\alpha \left(U_{s\mu} - pU_{q\mu}\right)\mu_\varepsilon + s_M M_\varepsilon > 0 \tag{3}$$

where term α is positive by concavity.

The above Proposition shows that emotions can influence the demand for sex at the intensive margin through three mechanisms. The first mechanism is intuitive: if higher emotional arousal increases the marginal utility of sex, it leads to greater demand for sex.

The second mechanism concerns the opportunity cost of buying sex, expressed in terms of the forgone marginal utility of the composite good. If emotions increase the marginal utility of q (e.g., alcohol consumption), the demand for sex decreases. This effect is more likely the higher the price of sex, because this would further increase its opportunity cost.

The third mechanism relates to windfall gains accruing to individuals who have bet on an unlikely but remunerative outcome. If an individual has bet on the unexpected outcome ($M_\varepsilon > 0$) and sex is a normal good, the unexpected windfall gain increases the demand for sex. If sex is an inferior good, instead, demand for sex decreases.

The effect of an unexpected outcome on the decision to buy any sex, i.e. the extensive margin of demand, can be understood considering an individual who is indifferent between buying and not buying, i.e. such that $U(s^*, M - ps^*) - \sigma = U(0, M)$. For such an individual, the effect of the unexpected outcome can be described as follows:

Proposition 2 (Extensive margin) *An individual is more likely to become a buyer of sex after an unexpected football outcome if*

$$\left(\Delta U_\mu - \sigma_\mu\right)\mu_\varepsilon + \Delta U_q \cdot M_\varepsilon > 0 \tag{4}$$

The choice at the extensive margin depends on three terms. Term $\Delta U_\mu := U_\mu(s^*, q^*) - U_\mu(0, M)$ describes the difference in the marginal utility of emotions, comparing the case in which some sex is bought with respect to the case in which no sex is bought. If this difference is positive, an individual is more likely to buy sex.

The second term σ_μ describes the effect of emotions on the stigma cost. If such a cost decreases because of, e.g., euphoria, sadness, or reduced stigma from the peers, an individual is more likely to buy sex.

The third term $\Delta U_q := U_q(s^*, q^*) - U_q(0, M) > 0$ is not related to the effect of emotions, but to the windfall gains from betting, if any. If the gap ΔU_q in the two marginal utilities of the composite good is positive, an individual who has won an unexpected income is more likely to become a buyer of sex.

In the following, we abstract from the role played by windfall gains.

Corollary 1 *In the absence of windfall gains from betting, after an unexpected football match outcome:*

- *An individual is more likely to become a buyer of sex if:*
  - *Emotional arousal increases the utility gap between buying and abstaining from buying sex, and*
  - *Emotional arousal reduces the stigma associated with buying sex*
- *Conditional on being a buyer, the quantity of sex purchased increases if:*
  - *Emotional arousal increases the marginal utility of sex,*
  - *The impact of emotional arousal on the marginal utility of the composite good is low, and*
  - *The market price of sex is low*

Note that the intensity of the responses at the intensive and extensive margin described in Corollary (1) are stronger, the greater the emotional response $\mu_\varepsilon > 0$ to the unexpected outcome.

4 Empirical Strategy

This section presents our identification strategy and our main results.

4.1 Identification

To estimate the effect of EPL and SP football matches on sex workers' transactions, price and duration, we estimate the following equation:

$$Y_{c,d} = \alpha_c + \alpha_d + \sum_{\mathrm{d}=-5}^{+4} \gamma_d \cdot \mathbb{1}_{c,d} + \varepsilon_{c,d} \tag{5}$$

where α_c and α_d are respectively county and year-by-day fixed effects. $\mathbb{1}_{c,d}$ is a binary variable that equals 1 if in county c on day d there is a football match and takes value 0 otherwise. In those counties and days where more than a game is played, the binary variable still equals 1.

In equation (5), Y is the variable of interest in county c on day d. We consider the number of transactions, the average price of transactions in pounds, the average duration of transactions in minutes or the ratio between price and duration. The first outcome is a count variable, and hence it is estimated through a Quasi-Poisson (also known as, Poisson Pseudo Maximum Likelihood, hereafter PPML) estimator, while the other three are transformed with the inverse hyperbolic sine (hereafter, IHS) and estimated with Ordinary Least Squares (hereafter, OLS) regression.

Consider regression model (5), γ_d for $d \geq 0$ are our coefficients of interest. According to our identification assumption, these estimates correspond to the causal effect of either the match taking place or the realization of a certain score. For $d = -5$ to -1, γ_d gives us an estimate of the pre-trends for the parallel trend assumption. In our setting, such an assumption states that in the absence of the treatment (no football games) and controlling for the set of fixed effects, the trends of the outcome variable would have followed the same trend between treated and untreated counties. In other words, the analyzed variables linked to sex work would have exhibited similar patterns in absence of the football match. To this extent, inclusion of β_c and α_d is paramount. Any difference taking place during all the sample period but varying at county level is controlled by β_c. While, any difference equals for all counties but varying at year-by-day level is captured by α_d.

Standard errors are clustered at county level to address the potential cross-correlations between units within the same geographical area. Note that the treatment variation in our specification is at county level since each game is linked to a home team and it only corresponds to a certain county. In the main specification we opt to narrow our event study in a 5-day window, therefore comparing the trend of the outcome variable in the previous 5 days in which it is not treated and in the 4 following days to the first treatment.[8] However, we also restrict to windows of 3, 2 and 1 days before and after to ensure the robustness of the results.[9]

We do not estimate the main outcome through OLS with the IHS transformation as Mullahy and Norton (2022) and Chen and Roth (2024) show that this setting is unit dependent, especially when there is an important number of 0s as in our case. In addition, Aihounton and Henningsen (2020) and De Brauw and Herskowitz (2021) have also raised concerns about how to interpret the magnitude of treatment effects estimated with such transformation.[10] Thus, for count data dependent variables we prefer using a PPML regression. To this extent, all our estimates should be interpreted as semi-elasticities.[11]

4.2 Main results

One potential concern is that the day on which a football match takes place might be somewhat predictable, given that these events are scheduled in advance. To address this, we estimate regression model (5) for two distinct categories of matches: those with expected results and those with unexpected results, based on betting odds. Unexpected results are defined as matches where the betting odds predicted a victory, but a defeat occurred, or vice versa—where a defeat was predicted, but a victory occurred. Conversely, expected results refer to matches where the betting odds correctly predicted the result—either a victory that materialized or a defeat that ultimately occurred.

This distinction serves a dual purpose. First, it enables us to concentrate on the regressions where the identification strategy is more plausible. While, the day of the

[8] This means that any day in which eventually a game happens in the previous 5 days is excluded from the pre-trends analysis.

[9] Since by FIFA directions there must be at least 48 hours between two games played by the same team. The specifications relying on 3 days or lower are the least conservative. Then, if our results hold with our baseline specification of 5 days, we expect to find similar results also for narrower time windows.

[10] Mckenzie (2023) provides an extended discussion on this issue.

[11] Note that for the IHS transformations, this is asymptotically true when N is large, while for PPML regressions, estimates should be interpreted as differences in log of expected counts (i.e. semi-elasticities).

match may be predictable to some degree, unexpected results are far more difficult to anticipate, thereby strengthening the plausibility of our identification approach. Second, it allows us to investigate whether the predictability of match outcomes influences the observed effects. This predictability is crucial, as it plays a key role in the formation of emotions, which are central to our analysis. By separating expected and unexpected outcomes, we can better isolate the emotional dynamics at play and their potential impact on the results.

Figures 5 and 6 respectively display the results for unexpected results and for expected results. They highlight that for unexpected results there is an increase in transactions on the day of the match and a reduction in expenditure and duration, with no change in the ratio between the two measuring the type of services, starting the day of the match and lasting for at least four days. While, for expected results there seem to be no clear effect on the considered variables.

In Figure 5, the increase in transactions occurs exclusively on the day of the match, making it difficult to determine whether this spike is directly caused by the materialization of the unexpected result. In contrast, the declines in expenditure and duration are observed both on the day of the match and in the days following it, suggesting that these effects may indeed be triggered by the unexpected outcome. When comparing these results to those in Figure 6, we find suggestive evidence that emotions could play a significant role in driving these patterns.

To further investigate this potential channel, we extend our analysis by dividing unexpected results into two mutually exclusive subcategories: unexpected losses and unexpected wins. This approach allows us to examine whether emotional responses to unexpected outcomes differ depending on whether the unexpected result of the home team is favorable (a win) or unfavorable (a loss). If emotions play a role, we expect the effect of these two subcategories to differ.

With this objective in mind, Figures 7 and 8, respectively, present the results for unexpected defeats and unexpected victories. The former figure illustrates that when an unexpected loss occurs, transactions exhibit a spike on the day of the match, while spending and duration decrease on that day and in the subsequent days. This pattern is not present when analyzing unexpected victories. This asymmetric piece of evidence between unexpected defeats and unexpected wins suggests that emotional channel dominates the pure game effect. Put it differently, it is not the organization of the match per se that affects consumer behavior of commercial sex but rather the outcome of the match.

All in all, our results hint at the notion that a share of football fans are customers of sex workers and after an unexpected loss they decrease the amount of money and time spent in sex workers' activity. However, the opposite behavior does not happen when their team succeeds. XXXXX till here

5 Further analysis

5.1 Robustness

This section explores robustness of our results. An important issue is to check whether different choices of functional form for our dependent variable affect our findings. Accordingly, we present results omitting PPML regression for transactions and the IHS transformation for expenditure, duration and ratio. Namely, we run OLS regressions with variables in levels for our four dependent variables considering events in which an unforeseen defeat occurs.

Results are presented in Figure A.1. As a whole, such results are aligned with our main estimates in Figure 7. As a matter of fact, they do not find a temporarily surge in transactions but they do find the strong decay in both expenditure and duration. These findings suggest our results are not due to the functional form used.

Moreover, we wanted to test whether our categorization of unexpected results could be driving our results. To check this, we followed the categorizations of Ivandić et al. (2024): "we classify a game as an expected win if the probability of winning assigned by the betting market was equal to or higher than 55%; as an expected loss if it was smaller than 45%, and as a close match if the estimated winning probability is in-between. The contrast between the ex-ante market prediction and the ex-post results makes it possible to further classify a football match as one of six distinct categories, depending on whether the end result was better or worse than the expected one. These are an upset loss, an upset win, a close loss, a close win, a predicted win, or a predicted loss".

Hence, we run two different tests: first we estimate a model that includes all the treatments and second we rely on a continuous specification.

Joint Treatments. We follow as closely as possible Ivandić et al. (2024) and Card and Dahl (2011):

$$\begin{aligned} Transaction_{it} = \gamma_1 CloseWin + \gamma_2 CloseLoss + \gamma_3 Exp.win + \gamma_4 Exp.Loss \\ + \gamma_5 Unexp.Win + \gamma_6 Unexp.Loss + \beta_c + \alpha_d + \epsilon \end{aligned} \tag{6}$$

Results are presented in A.2 and we can point that the increase in the number of transactions is driven by unexpected losses only. Moreover, the estimated coefficients are robust to the inclusion of fixed effect for game days, thus corroborating our findings[12].

Then, we estimate equation 5 only for unexpected losses, following this new categorization. The results, presented in A.5, closely resemble those of our main specification, which reassures us about the soundness of our findings.

Continuous Specifications. We now define the treatment not as a dummy but as a quantitative variable that proxies shock intensity. We define the shock intensity as the difference in the probability of a result for the home team over the away one, for wins and losses separately, in deciles. We then estimate the marginal effect of an additional unit of shock in a standard continuous difference-in-difference specification (Figure A.4) and with respect to the baseline control group *i.e.,* no games' county-by-day records (Figure A.3). Both panels show that the only significant estimates are at the highest level of shock, particularly, as Figure A.4 shows, for losses. Results suggest a sizeable effect, since the marginal increase in sex work transactions induced by an additional unit of shock for losses is 2 p.p.

5.2 Potential mechanisms

So far our results support the notion that an unexpected loss is reduces sex work activity. Our results might be explained by fans' behavior. In this section we explore whether this type of defeats might affect other features related to sex work activity. As it was presented in Section 2, we can further divide our data in out-calls, in-calls, "movers" and "stayers".

Our empirical findings suggest that unexpected losses affect in-calls and "movers" but there is no effect for out-calls and "stayers". Results are shown in Figure A.6. Un-

[12]Results available on request

expected losses increase transaction with in-call sex workers and "movers" sex workers. There might even be an intersection between these two categories. Stayers exhibit a positive estimated coefficient at $t = 0$ but it is not statistically different from zero.

White sex workers comprise about 80% of our sample. Yet, it might interesting to split the sample across this dimension as well. Figures A.7 and A.8 respectively present these results for transactions with white sex workers and non-white sex workers.

In this case, our findings suggest that the found increase in transactions is due to nonwhite sex workers. While the decrease in expenditure and ratio is due to white sex workers. In this case, there is even a decay in the ratio between the two. This piece of evidence suggests there might be a change in the requested services with white sex workers.

Taken together, these results suggest that unexpected losses decrease the money spent and duration of transactions with white sex workers, affecting potentially also the bought services but leaving unaltered the number of transactions with white sex worker. On the other hand, nonwhite sex works exhibit a temporary boost in transaction on the day of the unexpected loss but there is no effect on spending and duration of such transactions. We may further split the data across age categories but our results suggest unexpected losses do not affect any specific age group.[13]

Distance. We investigate heterogeneity between matches that happen at different distances. First, we build a match-specific dataset in which each observation is a premier and football league game for which we compute the linear distance between the home and the away teams' cities[14]. We believe that this may help to disentangle whether the effect is entirely driven by home fans, which should presumably be higher in distant matches since it is harder and more expensive to travel, or by both, that instead should happen more intensively in close matches where more away fans can come to the home team stadium. Results are displayed in Figure 14 clearly indicate that the effect is entirely driven by close matches, classified according to the median in the distance on the match-specific dataset. This suggests that a mix of away and home fans is the mechanism through which unexpected results and losses drive the increase in sex transactions. Home fans' unexpected disappointing shock and away fans' positive shock led to both

[13] Results are available upon request.

[14] For instance, Chelsea vs Arsenal distance is 0 km, while Liverpool vs Chelsea, and vice-versa, distances are 287 km.

alleviating and cheer exploiting sex services.

Sex Service Profile. We now investigate which type of sex services are correlated with each other and the increase in the aftermatch of matches. We exploit therefore information that so far we have not investigated. Sex services are classified into 8 categories: gender, anal, oral, oral without condom, sex, massage, cuddle, and kiss. We additionally exploit whether the service is an incall or an outcall transaction. To do that, we perform a cluster analysis on sex working records classified according to fee and duration, selecting ex-post as the best partition after several trials, that is with 3 clusters that we obtained with a k-means technique with Euclidean distance. Figure 15 maps the three groups by color by fee and duration. We then select the sex transactions belonging to the cluster with the lowest prices and duration (the yellow one in Figure 15), as we find in the event studies, and profile it according to the service mix. These records involve more frequently kiss, massage, oral, oral without condom, and are incall services.

We corroborate these findings by estimating our baseline identification on sex transactions, split by service type. Results are shown in Figure 16 that, coherently with the cluster results, indicate that the increase in the aftermath of unexpected losses is driven mainly by sexual foreplays rather than hard sex, which indicates that the clients have less time to spend on consuming sex. Combining these results with distance analysis, we believe that the empirical evidence suggests that away fans channel is the main driver behind the increase in sex transactions in the aftermath of unexpected soccer outcomes.

6 Conclusion

In this paper, we study how football matches trigger sex workers' activity. We find that football matches per se do not affect sex workers' activity. While, buying sex might be a coping mechanism in case of defeat, especially when it is not expected; but it is not a channel of celebration in case of victory.

Our results are robust to different specifications and suggest that the found effect is led by sex workers moving to the place of the customer. Our findings also suggest the effect differ across ethnicity. Transactions with white sex workers increase on the day of unexpected loss without affecting expenditure and duration. Yet, expenditure and duration with nonwhite sex workers reduce after an unexpected loss, affecting potentially also the purchased services.

Altogether, these results are coherent with an asymmetrical behavior of football fans that purchase different services related to sex work after a defeat takes place. Further research and finer data are needed to further shed light on the mechanism at stake.

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Tables & Figures

	Obs.	Mean	SD	Min	Max
Age	38,354	36.80	9.55	18	80
Duration of service (Min)	38,446	92.29	105.2	20	21600
Service fee (£)	38,808	247.0	233.9	12.24	13330
Hourly earning	38,446	176.3	118.7	1.34	13330
Incall	38,808	0.83	0.38	0	1
Ethnicity					
Arabic	38,804	0.00	0.04	0	1
Asian	38,804	0.02	0.14	0	1
Black	38,804	0.02	0.15	0	1
Chinese	38,804	0.00	0.07	0	1
Indian	38,804	0.01	0.08	0	1
South American	38,804	0.01	0.08	0	1
Mixed	38,804	0.03	0.18	0	1
Other	38,804	0.01	0.09	0	1
White	38,804	0.81	0.40	0	1

Notes: Age in years, duration in minutes, sex workers' wage adjusted to '23 CPI in £, ethnicity, and gender. An incall transaction takes place at the sex worker's place; an outcall at the customer's location. Data from '04 to '19.

Table 1: Descriptive statistics by sexual services type.

	Count	**Mean**	**SD**	**Median**	**Min**	**Max**
Duo	45,806	.0201284	.1404409	0	0	1
Female	45,806	.9750688	.1559173	1	0	1
Male	45,806	.0026634	.05154	0	0	1
Transexual	45,806	.0014409	.0379317	0	0	1
Travestite	45,806	.0006986	.0264221	0	0	1
anal	45,806	.1007728	.301031	0	0	1
oral	45,806	.503886	.4999904	1	0	1
OWO	45,806	.1561586	.3630096	0	0	1
sex	45,806	.8007685	.3994269	1	0	1
massage	45,806	.133083	.3396681	0	0	1
cuddle	45,806	.0854037	.2794845	0	0	1
kiss	45,806	.3989434	.4896864	0	0	1

Notes: Duo means having two or more well-defined orientations that the individual switches between. OWO indicates "oral without condom".

Table 2: Descriptive statistics of betting odds and implied probabilities.

Games:	**Obs.**	**Mean**	**Median**	**SD**
Home Win Odds	7,296	2.85	2.20	2.08
Away Win Odds	7,296	4.77	3.40	4.05
Home Win Probability	7,296	0.44	0.43	0.18
Away Win Probability	7,296	0.30	0.28	0.17

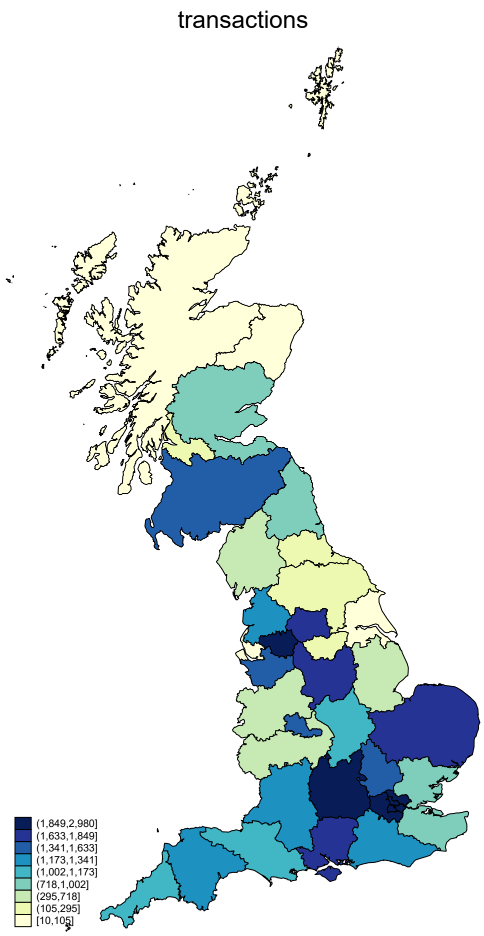
Notes: This table reports the descriptive statistics of the football dataset, presenting the betting odds and the probabilities of outcomes of all Premier and Scottish leagues matches from '08 to '19.

Table 3: Staggered Event Study estimates of unexpected losses on transactions.

	(1) *transactions*
Average Tot Effect (ATE)	0.226**
	(0.111)
Joint Pre-trend p-value	0.379
Observations	7,587
County FE	Y
Year x day FE	Y

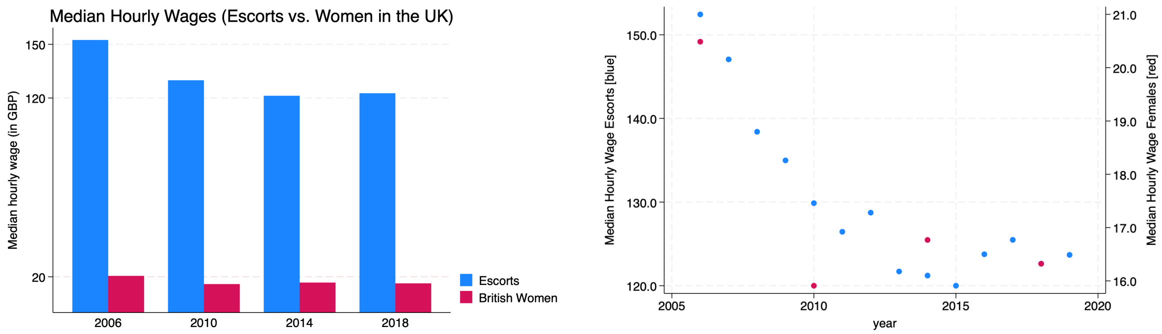
Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports results for the estimation of equation (5) using the de Chaisemartin and D'Haultfœuille (2024) estimator. Standard errors are clustered at the county level. The number of obs. reduces as the estimator by default considers only the first treatment for each unit plus the untreated 5-days before and after to compute the placebo and the dynamics effects. In other words, the estimator does not yield the causal effect of all unexpected games, but only of the first unexpected game for each county. For an extended discussion on this feature, we redirect to de Chaisemartin and D'Haultfœuille (2024).

Figure 1: Map of sex work transactions across UK counties.



Notes: The map displays the number of sex work transaction records across UK counties between 2008 and 2019. The sample entails England and Scotland, while Wales is discarded.

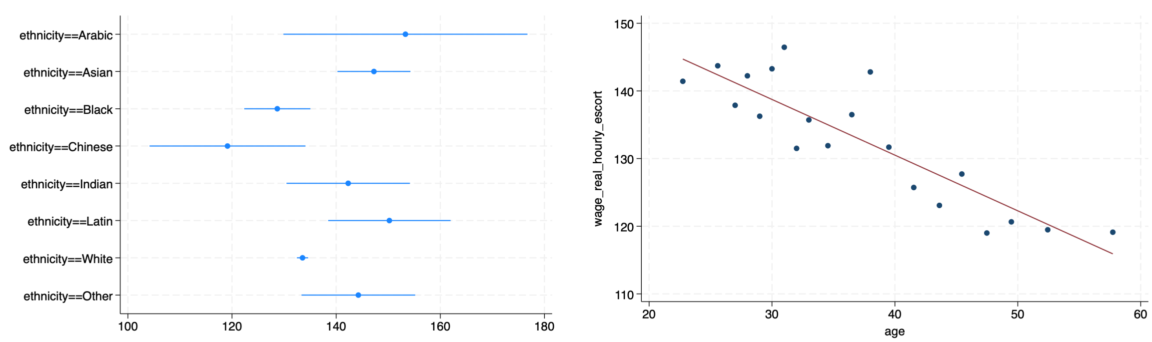
Figure 2: Female sex workers earnings compared to the female median hourly earnings in the UK.



(a) Ethnicity. (b) Age.

Note: Panel (a) displays the median hourly earnings in GBP for women in the United Kingdom (red) and the median hourly earnings of sex workers in our dataset (blue) between 2006 and 2019 are compared in this figure. Panel (b) displays instead the same earnings across more years. Earnings are deflated to 2015 prices. Female earnings are from Eurostat, and sex worker services are from our dataset.

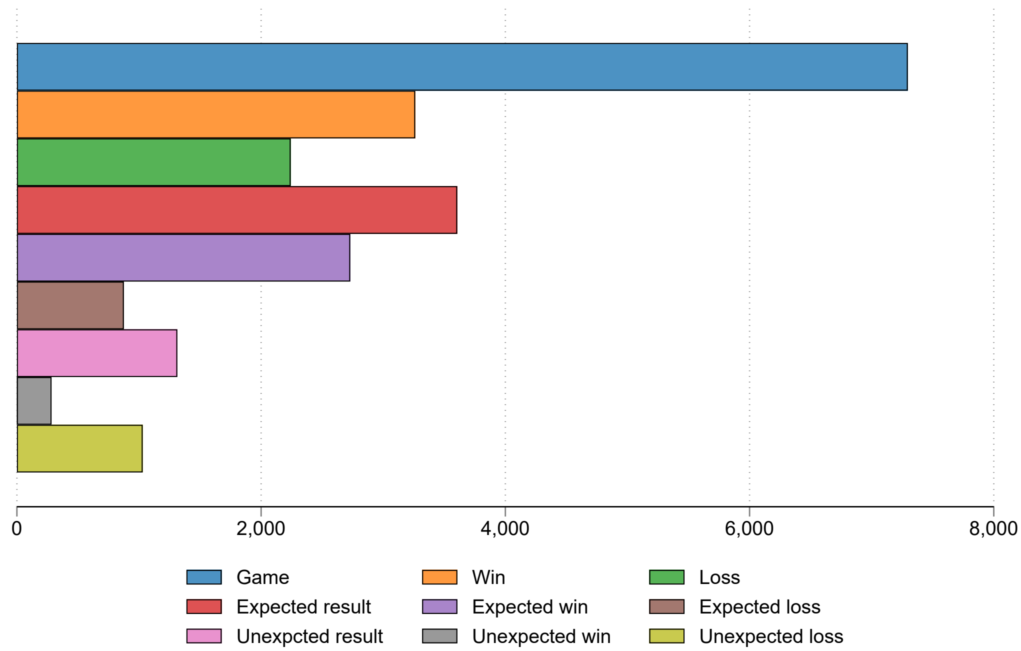
Figure 3: Sex workers' earnings by ethnicity and age.



(a) Ethnicity. (b) Age.

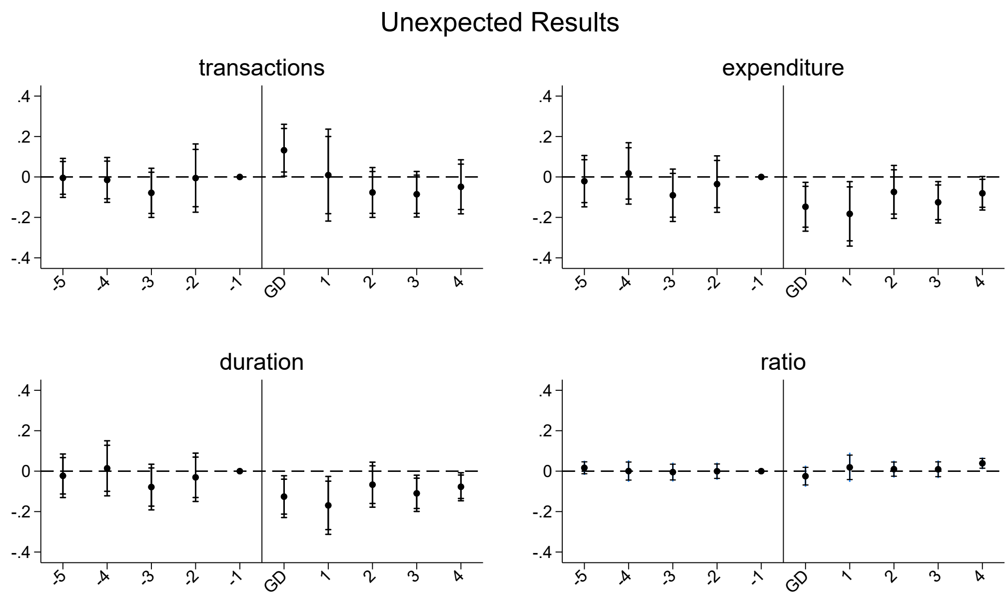
Notes: 95% confidence intervals displayed. Estimates are based on all years of the dataset.

Figure 4: football matches by actual and ex-ante predicted outcomes.



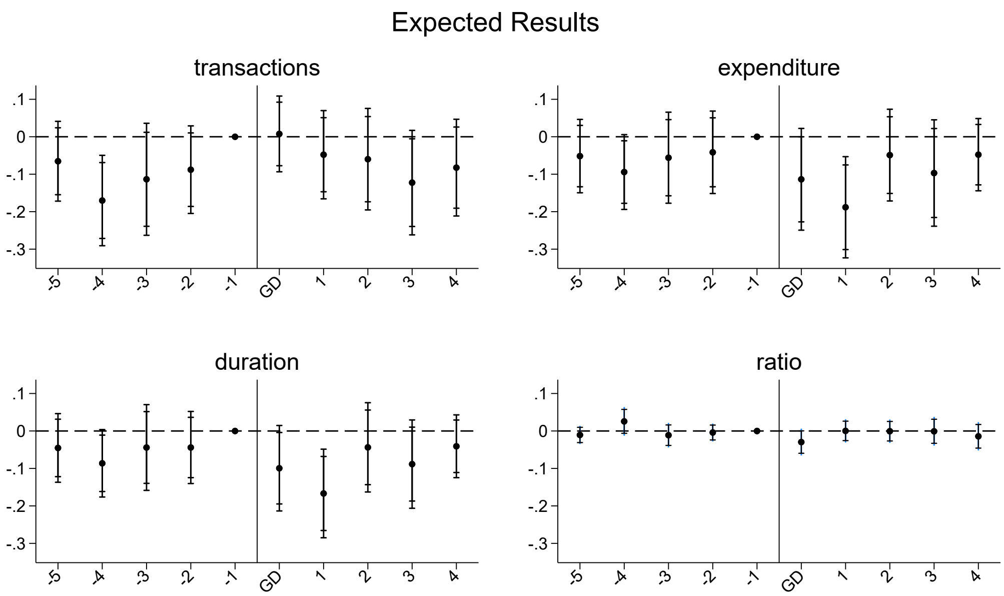
Notes: The figure displays the results for all the 7,296 football matches in our dataset. Details on the classification between expected and unexpected results are in Section 2.1.

Figure 5: Event studies for the effect of unexpected results on transactions, expenditure, duration and ratio between expenditure and duration



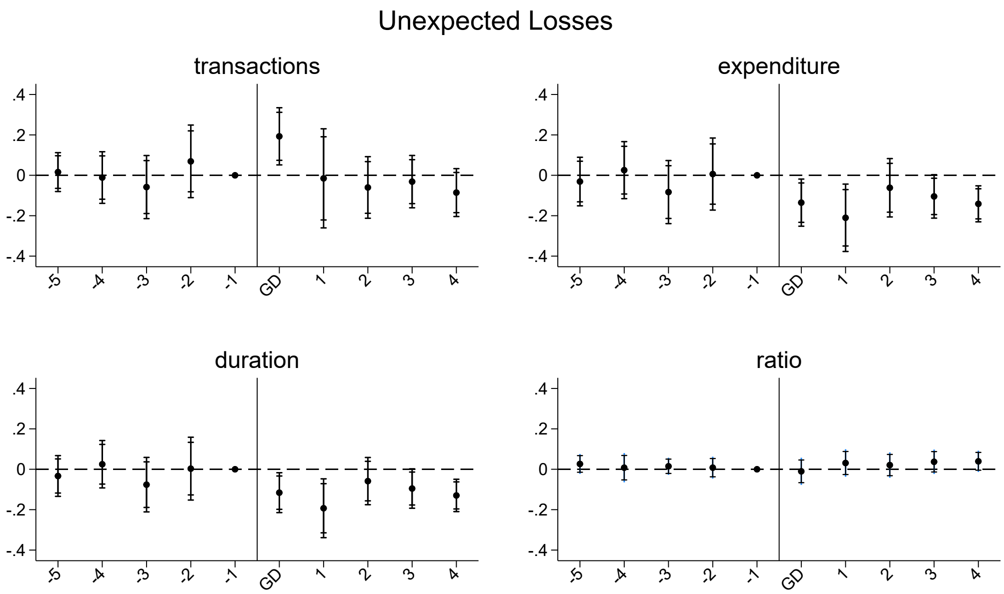
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 6: Event studies for the effect of expected results on transactions, expenditure, duration and ratio between expenditure and duration



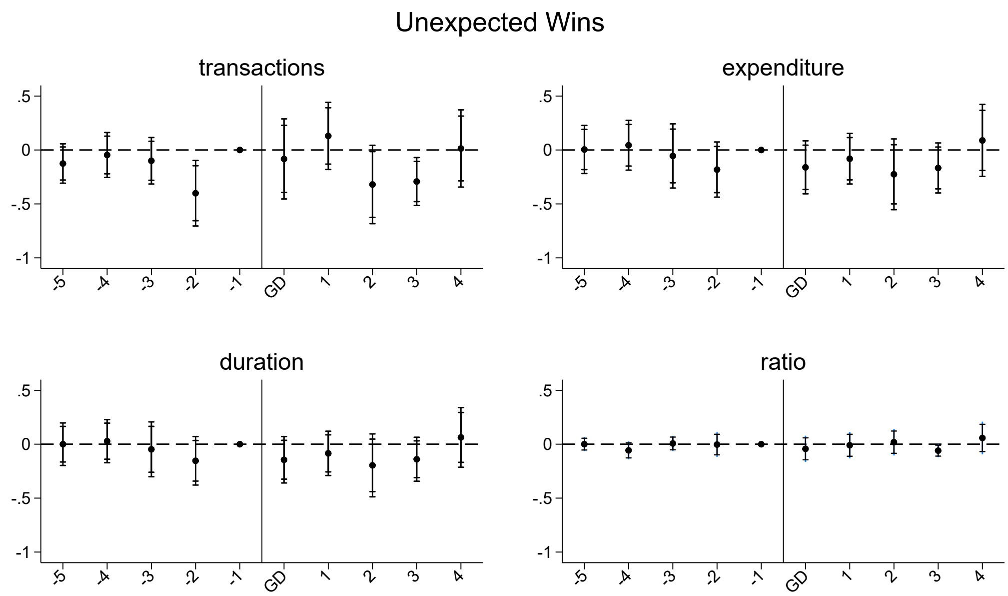
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 7: Event studies for the effect of unexpected losses on transactions, expenditure, duration and ratio between expenditure and duration



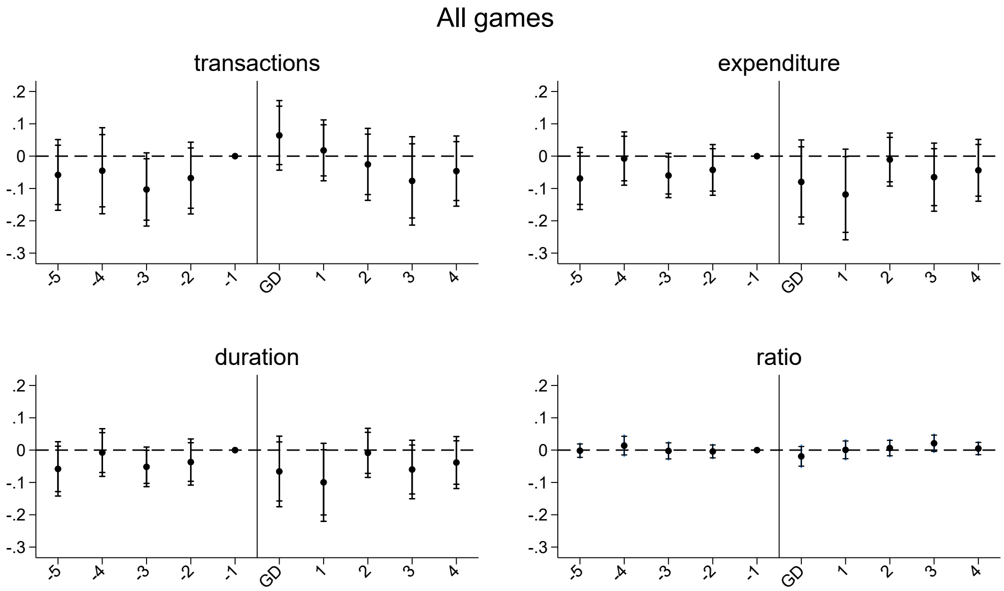
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 8: Event studies for the effect of unexpected wins on transactions, expenditure, duration and ratio between expenditure and duration



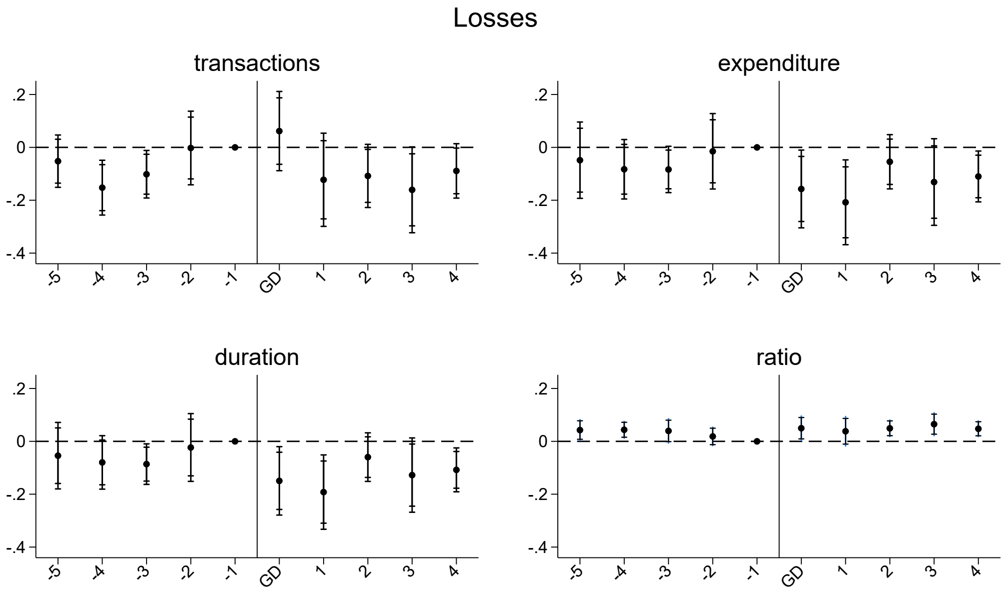
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 9: Event studies for the effect of all games on transactions, expenditure, duration and ratio between expenditure and duration



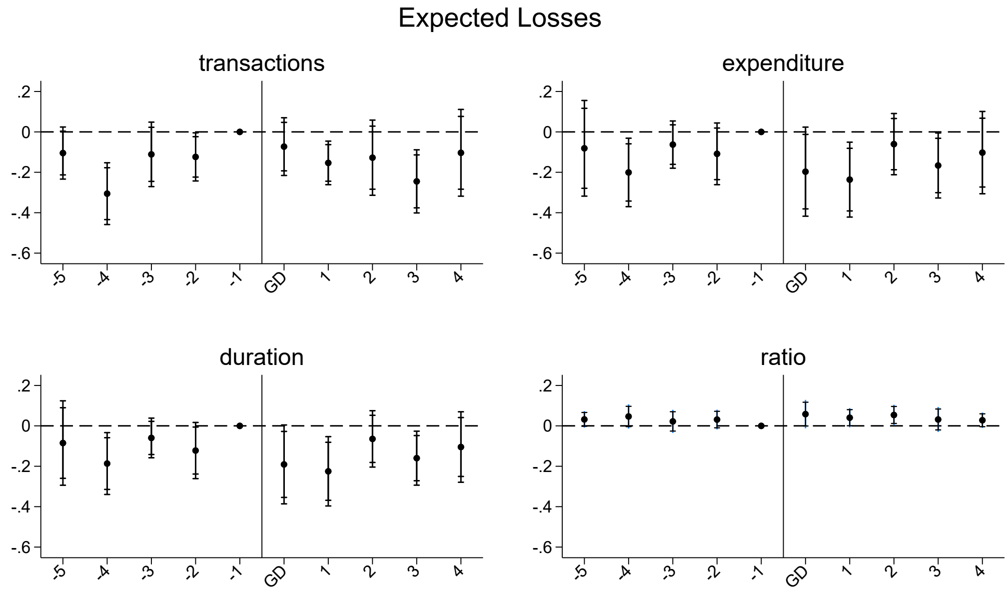
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 10: Event studies for the effect of losses on transactions, expenditure, duration and ratio between expenditure and duration



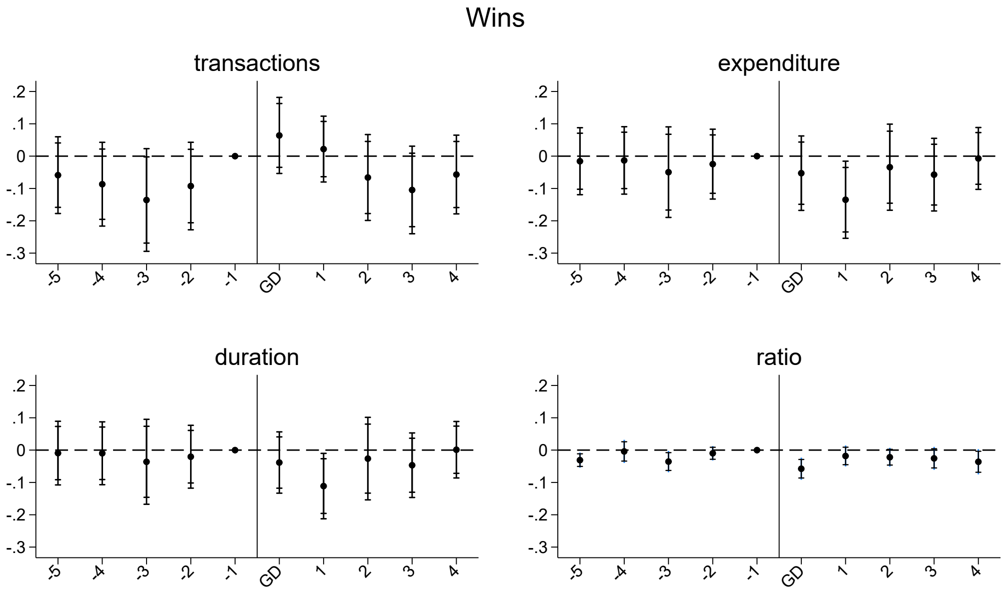
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 11: Event studies for the effect of expected losses on transactions, expenditure, duration and ratio between expenditure and duration



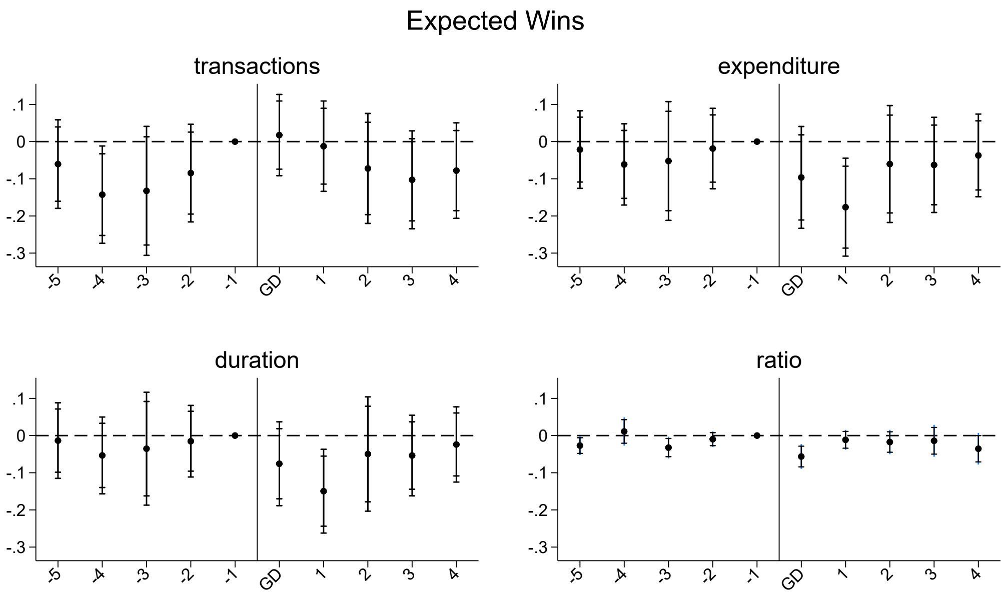
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 12: Event studies for the effect of wins on transactions, expenditure, duration and ratio between expenditure and duration



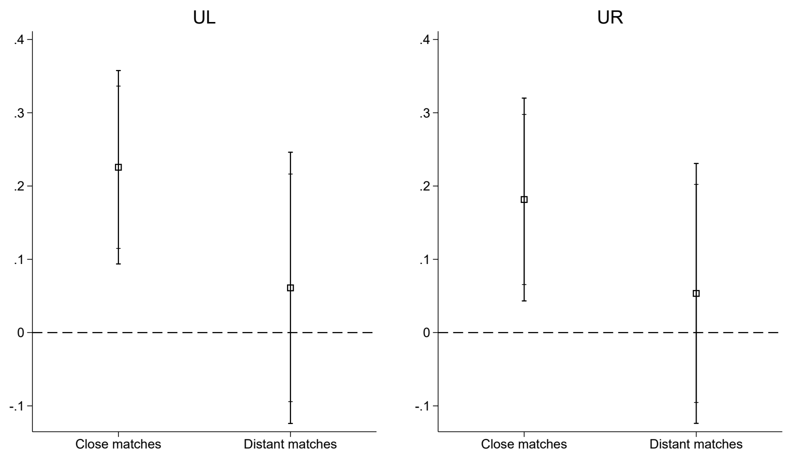
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 13: Event studies for the effect of expected wins on transactions, expenditure, duration and ratio between expenditure and duration



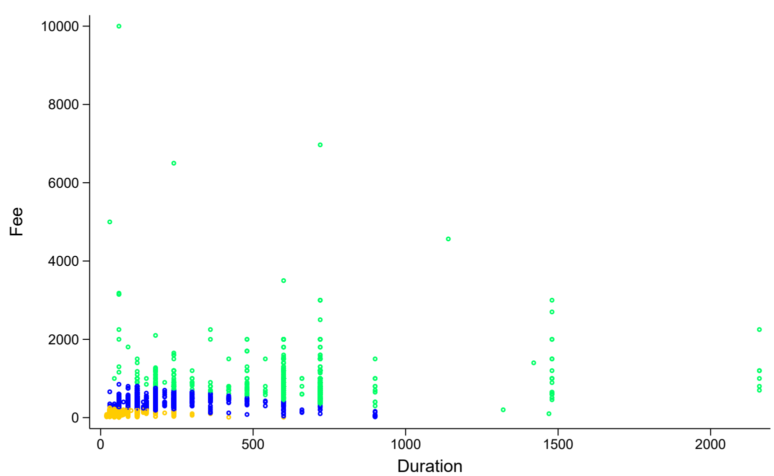
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transaction by county-day and OLS for expenditure, duration and the ratio between the two. Confidence intervals are estimated at 95% and 90% level. Standard errors are clustered at county level. Observations are 368,088. 95 and 90% CI displayed.

Figure 14: Heterogeneous estimates on transactions between close and distant matches by unexpected losses and results.



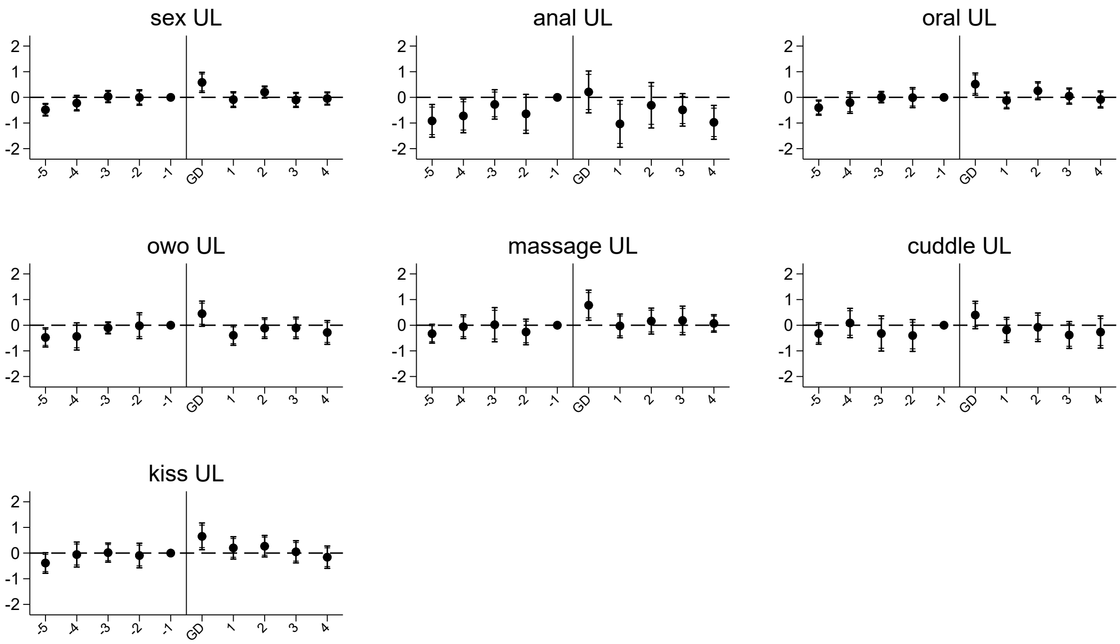
Notes: Distance is the linear distance between cities where each team is based in km and is match-specific. We later dichotomized it on the median.

Figure 15: Scatterplot of sex records by fee, duration, and cluster between 2008 and 2019.



Notes: Sex records are 45,383 non-missing observations aggregated into three clusters through a k-mean single-linkage Euclidean distance technique on fee and duration. We select three clusters because, by doing many trials, this is the best partition ex-post.

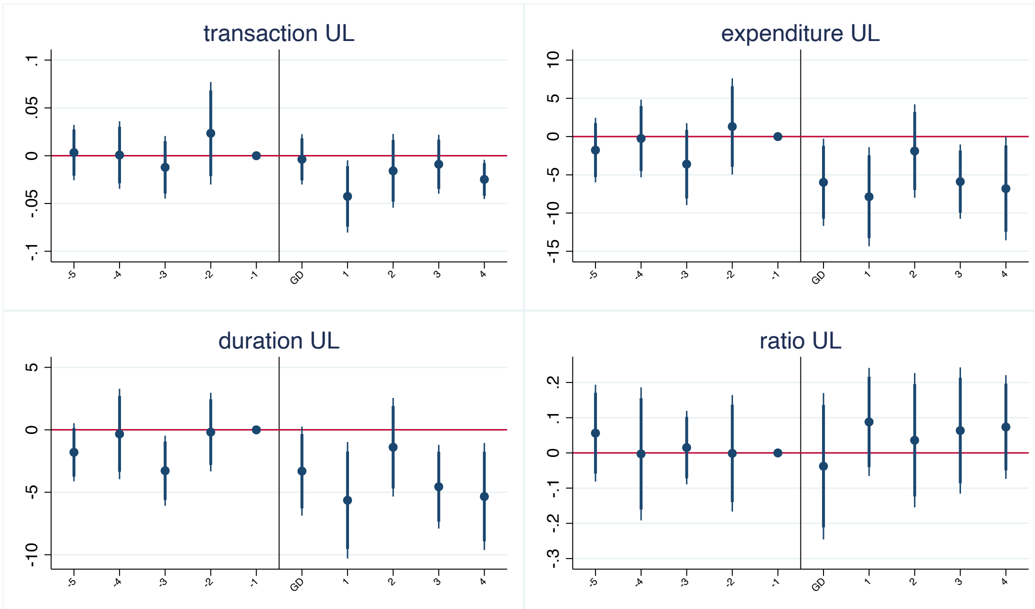
Figure 16: Event studies of unexpected losses on transactions by service type.



Notes: Sex records are 45,383 non-missing observations. OWO means "oral-without-condom".

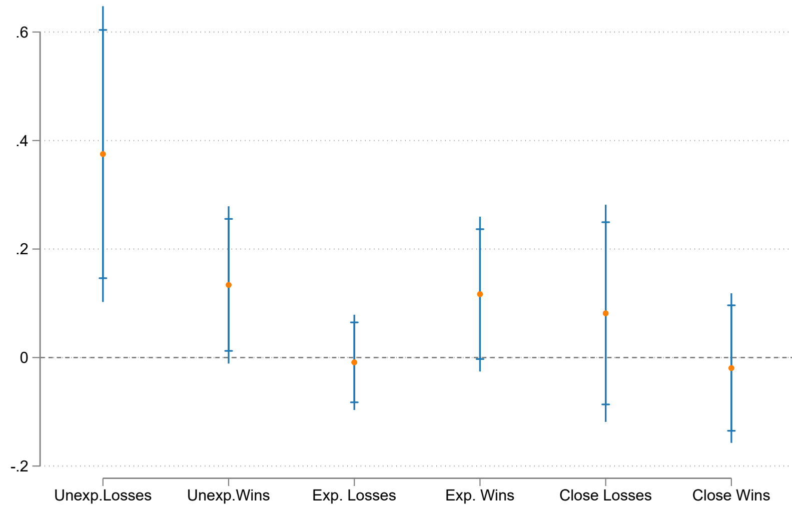
A Appendix

Figure A.1: Event studies for the effect of unexpected loss on transactions, expenditure, duration and ratio of expenditure to duration



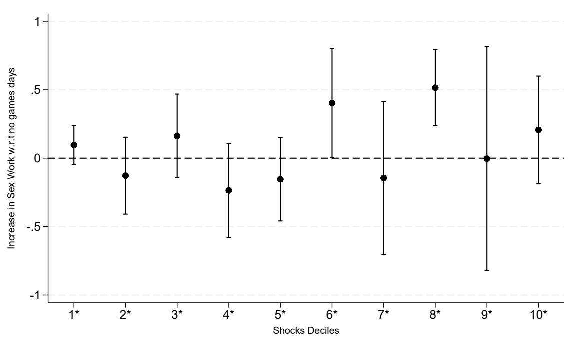
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transaction by county-day and OLS for expenditure, duration and the ratio between the two. Standard errors are clustered at county level. Observations are 368,088. 95 and 90% CI displayed.

Figure A.2: Replication of Ivandić et al. (2024) main specification on transactions

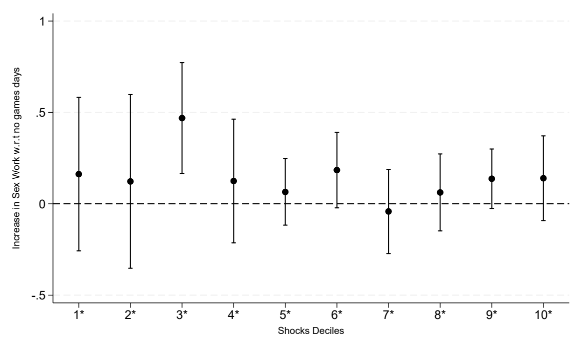


Notes: This figure shows the estimates of equation (5) using a PPML estimator, where the dependent variable is the number of sex work transactions. We estimate the combined effects of joint treatments during game days only. We categorize results as in Ivandić et al. (2024). 95 and 90% CI displayed.

Figure A.3: Game day effects of surprise "doses" on transactions.



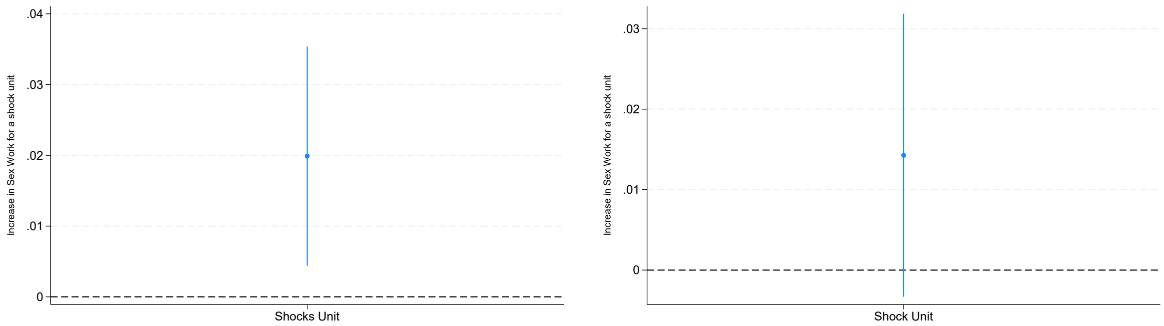
(a) Losses, from expected to unexpected.



(b) Wins, from unexpected to expected.

Notes: PPML estimates of deciles of surprise on sex transactions on game days. Surprise is rescaled in deciles from 1 to 10 (*i.e.,* low to high shock). In Panel (a) low deciles indicate highly expected losses, high deciles indicate low expected ones; the opposite in Panel (b). 95% CI.

Figure A.4: Game day effects of surprise ”doses” on transactions.

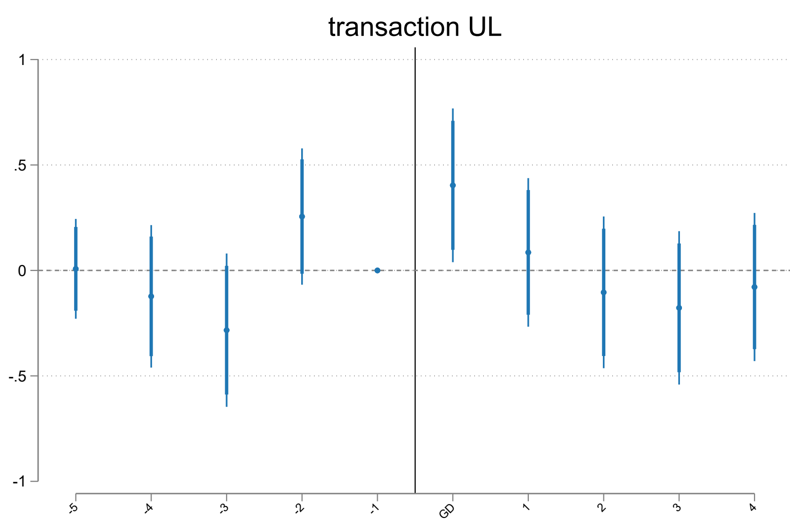


(a) Losses.

(b) Wins.

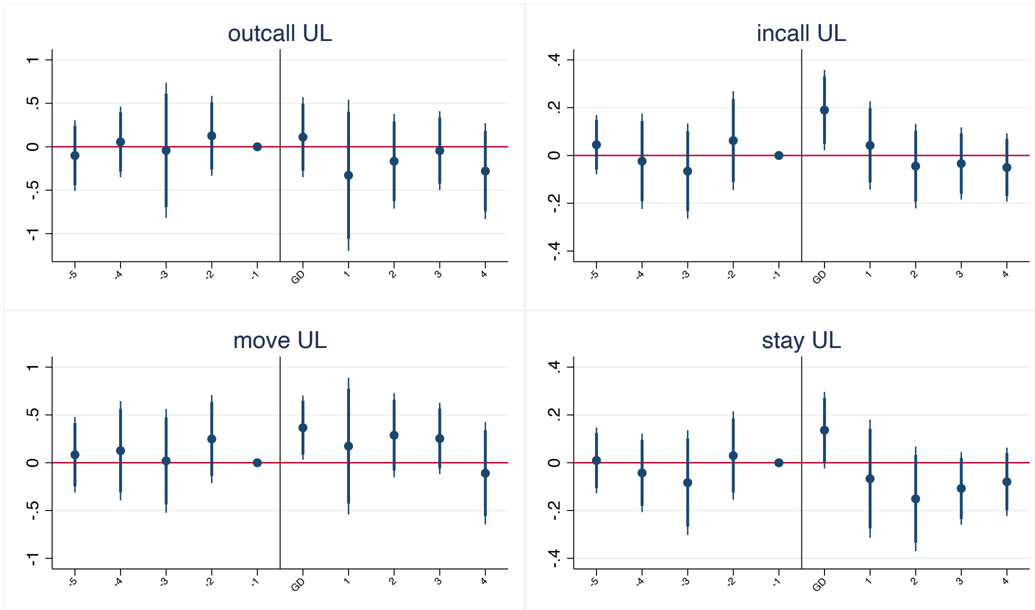
Notes: PPML estimates of a shock unit on transactions. 0 no games; 1 to 10 shock doses. 95% CI.

Figure A.5: Replication of equation (5) for unexpected losses following Ivandić et al. (2024)



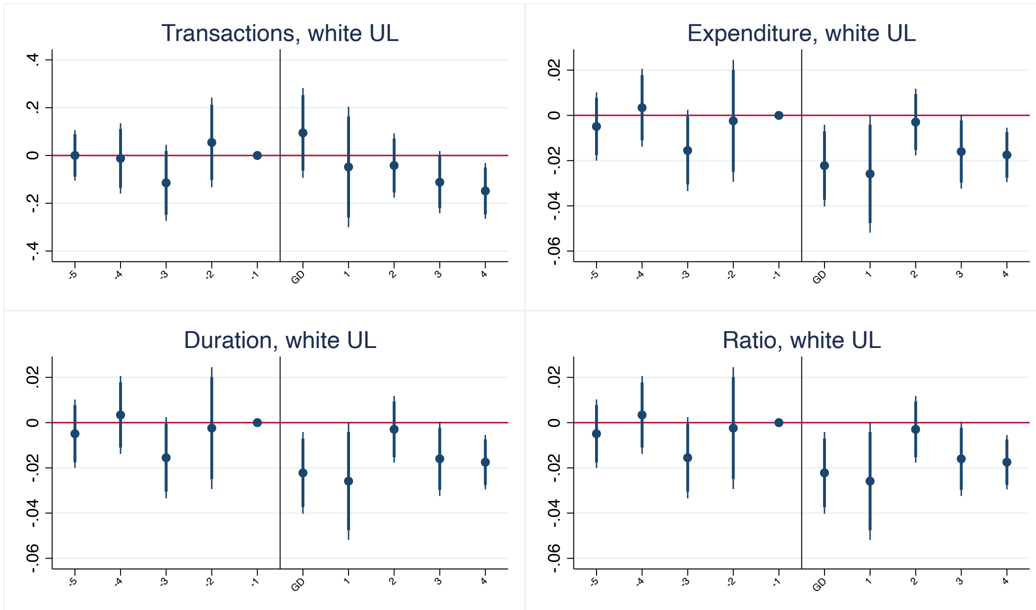
Notes: This figure shows the estimates of equation (5) using quasi-Poisson where the dependent variable is the number of transactions. We categorize unexpected losses as in Ivandić et al. (2024): namely a home defeat with an ex-ante home team's winning probability greater than 55%. 95 and 90% CI displayed.

Figure A.6: Event studies for the effect of unexpected loss on transactions, expenditure, duration and ratio of expenditure to duration



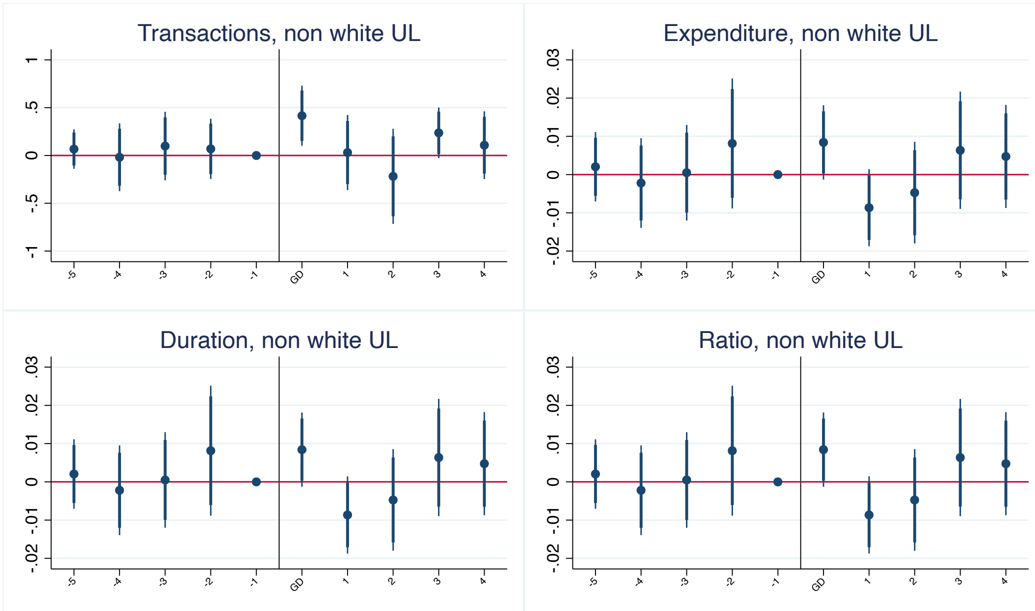
Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure A.7: Event studies for the effect of unexpected loss on transactions, expenditure, duration and ratio of expenditure to duration for white sex workers



Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.

Figure A.8: Event studies for the effect of unexpected loss on transactions, expenditure, duration and ratio of expenditure to duration for nonwhite sex workers



Notes: This figure shows the estimates of equation (5) using quasi-Poisson for the number of transactions by county-day and OLS for expenditure, duration and the ratio between the two. Standard errors are clustered at the county level. Observations are 368,088. 95 and 90% CI displayed.