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The Role of Uncertainty on Nondurable Goods: The Impact of (Hyper) Inflation in Argentine Football

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Abstract

Does uncertainty postpone consumption or destroy it? For durable goods, real options favor postponement. We study the effect of uncertainty on a perishable good, football attendance, in Argentina, a highly volatile economy, between 1967 and 1999. A one-standard-deviation increase in inflation uncertainty reduces attendance by 15.8 percent on impact, and by 19.45 percent once attendance habits adjust. Results are robust to alternative uncertainty measures and survive conditioning on inflation's level. Counterfactuals imply losses of 29 to 48 percent in the worst uncertainty episodes. Political turmoil (war, military coups) has no detectable effect. Uncertainty destroys nondurable consumption.

Keywords: Inflation uncertainty; nondurable consumption; football attendance; habit persistence; Argentina

JEL codes: D12; D81; E31; N16; L83; Z21

INTRODUCTION

Uncertainty, in its modern sense, dates back to the 1920s, when Frank Knight defined it as "people's inability to forecast the likelihood of events happening" (Bloom 2014, p. 154). In an overwhelmingly macro-oriented literature, the definition has withstood the passage of time. Jurado, Ludvigson, and Ng (2015, p. 1177) state that uncertainty is "typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents."

Indeed, much of the literature focuses on measuring uncertainty and relating it to its macroeconomic effects. It shows that when uncertainty rises (measured in various ways, currently lacking a consensus), output, investment, hiring, and consumption contract persistently (Bloom 2014; Carriero, Clark, and Marcellino 2018; Bianchi, Kung, and Tirskikh 2023).

Beyond the macro uncertainty literature, ample interest also focuses on its impact on individual industries, firms, and plants. For instance, evidence suggests that uncertainty is negatively related to bank lending (Buch, Buchholz, and Tonzer 2015; Valencia 2017), with uncertainty proxied by the dispersion of some relevant variable, ultimately impacting macro aggregates. At an even more disaggregated level, evidence, though smaller in magnitude, also suggests that price volatility relates to recessions.

Theoretically, real options theory formally demonstrates why agents delay investment when volatility (uncertainty) rises (Bloom 2014; Kellogg 2014). As Dixit and Pindyck (1994) establish, this dynamic is driven by the option value of waiting. When an investment is difficult to reverse but easy to postpone, the ability to wait for new information has tangible value. Once an agent commits the capital, the cost is sunk, and this flexibility is permanently lost. Consequently, as uncertainty increases, the value of keeping that option open rises, incentivizing firms to delay capital outlays until the future becomes clearer. For instance, the extent to which firms respond to changes in uncertainty in the oil drilling industry (Kellogg 2014).

This real options channel impacts firms as much as it affects households, but it makes durable goods a limited lens for evaluating underlying consumer demand. Like corporate capital expenditures, durables such as a house or a car are stocks bought infrequently in large, costly-to-reverse increments. When

uncertainty spikes, the dominant household response is not necessarily a reduced desire for the good, but a rational decision to preserve their option value of waiting. By postponing an irreversible commitment, consumers avoid sinking costs before macroeconomic conditions stabilize. This is the real-options channel, which explains why durable purchases fall sharply when uncertainty spikes, as it did following the Great Depression (Romer 1990). While some general equilibrium models suggest that agents will eventually recover this consumption once uncertainty resolves (Ejarque 2009), the immediate collapse reflects a strategic retiming of a lumpy stock adjustment rather than a genuine compression of demand.

It turns out, however, that most of what households consume is not postponable durables but nondurables such as food and entertainment. In this case, waiting is not really an option. Along this line of research, evidence suggests that, beyond the debate on durables, income uncertainty reduced spending on nondurable goods following the Great Depression (Greasley, Madsen, and Oxley 2001).

Literature on the role of nondurables under uncertainty is relatively scarce and, for the most part, focuses on developed economies, despite the greater significance of uncertainty in developing economies. Developing economies are structurally more volatile: their growth, exchange rates, and prices fluctuate far more than those of rich countries, so the uncertainty households face is correspondingly higher.

A traditional uncertainty indicator, for the case of advanced economies, is some stock price volatility proxy (Romer 1990; Greasley, Madsen, and Oxley 2001). This type of data is less representative for developing economies because stock markets are typically underdeveloped. To measure uncertainty, we need a series that becomes harder to forecast as its volatility grows (Bloom 2014). Indeed, in economies where prices move erratically, inflation dispersion is a leading source of uncertainty and its most visible expression. When households cannot predict what their nominal income will buy next month, they cannot easily plan how to spend it (Fountas, Karanasos, and Kim 2006). This is what makes the volatility of inflation a natural and economically meaningful measure of the uncertainty agents confront, a barometer of how hard it has become to plan.

This paper quantifies the impact of uncertainty on a novel nondurable good in an extremely volatile environment. Rather than the real options channel typical of durable goods, the precautionary channel holds

that consumers can adjust spending and saving to better sustain consumption under uncertainty (Alfaro and Park 2025).[1] In particular, we study uncertainty on football attendance in Argentina because it is nondurable and perishable in the strongest possible sense: a given match is played once, at one moment, and is then gone forever.[2] A household that stays home this Sunday cannot store the option and consume the same match later.[3] The consumption is simply forgone. The postponement margin that dominates the durables does not exist, and any response of attendance to uncertainty, instead of retiming, must be the pure, contemporaneous demand response, operating through income and precautionary channels that the durables literature cannot disentangle.[4] Football thus isolates exactly the part of the consumption response to uncertainty that matters for most of the economy, and that is the hardest to observe. Given its high frequency with recurring matches week after week across long seasons, the demand is continuously observed rather than captured at rare adjustment points. Hence, it is possible to determine how attendance moves with uncertainty and cleanly identify any shock.

[1] Vavra (2014) shows that the dispersion of price changes increases during recessions and correlates with firms adjusting more frequently, attributing these findings to increases in firm-level volatility. Higher volatility induces more firms to adjust prices, implying that a nominal shock is absorbed by the price level rather than by real output. In our setting, prices are fully (or nearly fully) flexible given the prevalence of high or hyperinflation during most of our sample period, leaving no margin for Vavra's mechanism to operate. Accordingly, changes in aggregate price flexibility cannot explain any relation between inflation uncertainty and attendance.

[2] Football in Europe and Latin America, soccer in the United States.

[3] Given that during our sample period there was no systematic TV broadcasting of the league, there was no substitute for attending the game.

[4] If season tickets were significant, the nondurable argument of a game might revert to a discussion of the durable status of such a purchase. However, during our sample period, season tickets were close to negligible.

The external validity of our findings depends on football being significant both economically and socially. We argue that in Argentina, football is deeply embedded in culture and society, making it a significant consumption good whose effects can explain households' overall preferences.

This paper addresses the gap in understanding the role of uncertainty over a nondurable good using the extremely volatile case of a developing economy, such as Argentina. Between 1967 and 1999, our sample period is close to an ideal laboratory: it lived through recurrent inflationary crises, including hyperinflationary periods, sharp and repeated changes in economic regime, and sustained instability, including military coups and the 1982 Malvinas War. This provides sudden, datable breaks against which to identify consumer behavior, and this exceptional variation is matched with a long, high-frequency history of football attendance, a significant and relevant consumption good in Argentina. The ultimate goal is to understand how consumers respond to these large exogenous shocks.

To quantify the effect of uncertainty on football attendance, we estimate a fairly conventional demand function for Argentine football in the form of Coates, Humphreys, and Zhou (2014). The estimation controls for uncertainty (the variable of interest) and political turmoil, including military regimes, dictator changes, and the Malvinas/Falkland war. It also controls for the uncertainty of outcome hypothesis (UOH; Rottenberg 1956; Neale 1964) and other match-related and team-performance variables that affect attendance.[5] Prices, calculated implicitly from the relation between gate revenues and attendance, are endogenous. Given that the elasticity is but a control, not of particular interest in our setup, and that the demand equation in sports cannot be identified as discussed in detail by Noll (2013), the best approach is to impose a value on the price elasticity rather than estimating it without prices as done in most of the sports economics literature.

The case of Argentina, a developing economy operating under extraordinarily volatile conditions, serves as an illustrative case for understanding how uncertainty can affect household consumption of a

[5] In the sports economics literature, the UOH is the idea that fans prefer to attend games where the final result is uncertain, that is, when the opposing teams have similar quality levels.

significant and culturally important good. Our main result is that, using our preferred uncertainty measure, a one-standard-deviation increase in uncertainty reduces attendance by 15.8 percent, regardless of specification. As attendance is habit-forming, the effect evolves over subsequent matches. Once habits adjust, a sustained one-standard-deviation increase in uncertainty lowers attendance by 19.45 percent, roughly 1,342 fans per match. The results, that attendance responds to the unpredictability of inflation, are robust to alternative uncertainty measures. Importantly, the results remain when we condition attendance on the level of inflation, showing that fans are drawn away from the stadium not by inflation itself, but by their inability to anticipate it. Using our preferred specification, we quantify the overall effect relative to observed attendance. During the extraordinary high-inflation periods Argentina experienced in the 1970s, the 1980s, and the early 1990s, the share of spectators who did not attend stadiums due to uncertainty was 29.92, 30.88, and 47.89 percent of observed attendance, respectively. The general conclusion is that the impact of uncertainty on households consuming nondurable goods is statistically and economically significant. Lastly, because we find no impact of the political turmoil that hit the country during our sample period (war and military coups), we conclude that economic uncertainty, rather than political turmoil, is the main driver of household nondurable goods consumption. The quantitative effects are, of course, specific to Argentina. Still, the qualitative results robustly show that in a developing economy context, economic uncertainty can shape household consumption decisions, ultimately affecting the overall economy.

ARGENTINA: FOOTBALL, POLITICS, AND THE ECONOMY

Using football attendance as a nondurable good is valid as long as it is a significant good for Argentine households. For football fans, there is no denying that football is deeply embedded in Argentine culture and society. For non-football fans, the Argentine film, *The Secret in Their Eyes*, is a brief summary of what it represents. Benjamín Espósito, a court investigator in 1974, struggles to locate the prime suspect in a major murder case. Isidoro Gómez, the suspect, went into hiding and remained at large for over a year, leaving the case effectively cold. The breakthrough comes when Espósito's assistant, Sandoval, reading the suspect's old letters, recognizes that a string of seemingly meaningless names are in fact the players of

Racing Club de Avellaneda, among the five most popular clubs in Argentina. Espósito and Sandoval figured that Gómez was a die-hard supporter of that club. Assuming a man can change his face, his home, his family, his name, even his God, but can never change his true passion, the detectives reasoned that no matter how well Gómez hid, he couldn't stay away from his team. Consequently, they decided to attend Racing's matches, eventually spotting him in the crowd during a Huracán–Racing fixture at the Tomás Adolfo Ducó Stadium. A goal sparks pandemonium, Gómez runs, and a frantic chase ends with his capture on the pitch itself. Indeed, the movie's plot is not just an isolated case but a reflection of what football represents for Argentine society.[6] There is little, if any, doubt that the demand we measure is economically and socially significant in its own right.

Political Evolution

Argentina's political trajectory between 1967 and 1999 is characterized by chronic instability and deep societal divisions. To understand this period, we must go back a few decades, starting with the Currency Board's closure in 1929 and the 1930 military coup, which paved the way for a turbulent period that would define much of the country's twentieth century.

The 1943 military government brought Colonel Juan Domingo Perón to power. Arguably, for better or worse, the most prominent figure in the Argentine political spectrum, "Nothing would be the same after Colonel Peron stood in front of the Town Hall (*Consejo Deliberante*) building, now converted into the secretary of labor, and harangued the workers" (Cortés Conde 2013, p. 122). Perón's victory in 1946 marked the beginning of a new era, but "in September 1955 . . . Perón was removed from power by a civilian-

[6] Around 5.5 million people received on the streets of Buenos Aires the Argentine national team that won the 2022 FIFA World Cup (https://www.fifa.com/es/articles/el-campeon-del-mundo-llego-a-casa-y-argentina-recibe-la-copa-mas-linda, accessed 21 July 2026). In contrast, two million people received the Spanish national team in Madrid after winning the 2026 FIFA World Cup (https://as.com/futbol/mundial/nuestro-exito-es-vuestro-exito-f202607-n/, accessed 21 July 2026).

military coup d'etat, although he still had broad popular support. This event initiated a stage of political instability in Argentina, which led in the end to the military dictatorship of 1976" (Rapoport 2005, p. 60).

Peronism was banned between 1955 and 1973, creating deep societal divisions. During those 18 years, Argentina experienced alternating weak civilian governments and military interventions. Civilian leaders like Frondizi and Illia faced "thirty-two attempted military coups, the last a successful one, which overthrew the government in 1962" (Cortés Conde 2013, p. 195). This cycle of instability continued until 1973, when the military allowed elections, and Perón returned to power after an 18-year exile. However, "the Peronist government of the seventies, which returned with popular support after the military left power in 1973, soon encountered internal contradictions which became more acute with Perón's death" (Rapoport 2005, p. 60).

The military dictatorship represented the most authoritarian period in Argentine history, lasting until the defeat in the Malvinas/Falklands War (see Table 1). Democracy returned in 1983 with "constitutionally elected President Raúl Alfonsín, bolstered by overwhelming support for democracy" (Cortés Conde 2013, p. 246).

[Table 1 about here]

Economic Evolution and Currency Transformations

Argentina's economic development during the twentieth century is intrinsically linked to political upheavals and marked by persistent inflationary pressures. The establishment of exchange controls in October 1931 marked the beginning of state intervention in the economy, as "all transactions in foreign currency had to be done henceforth through authorized banks in the Federal Capital" (Cortés Conde 2013, p. 86).

The Peronist era (1946–1955) brought significant structural changes, including the nationalization of public utilities and massive state intervention. However, these policies led to mounting inflationary pressures that would plague Argentina for decades to come. "By 1973–1974, the substantial political

authority of Peron after his return and the fabulous terms of trade could only afford one year of very precarious stability" (Gerchunoff and Llach 2009, p. 418).

The 1970s witnessed the first major currency reform, when the Peso Ley replaced the Peso Moneda Nacional at a rate of 100:1 in 1970 (Table 2). Inflation accelerated dramatically, and "the first quasi-hyperinflationary blast in 1975" eventually forced the introduction of the Peso Argentino in 1983 at a rate of 1:10,000 Pesos Ley (Gerchunoff and Llach 2009, p. 418).

The military government attempted economic liberalization but created massive currency overvaluation through its exchange rate policy. This led to "the huge burden of the foreign debt that rose from 8 billion dollars in 1975 to 45 billion in 1983, when the military dictatorship left power" (Rapoport 2005, p. 63).

[Table 2 about here]

The return to democracy brought new challenges. President Alfonsín's government faced mounting inflation, leading to the introduction of the Austral in 1985. "Alfonsín addressed the Argentine people, announcing a far-reaching plan to 'put an end to inflation and save democracy'" through "substitution of the peso with a new national currency, the austral" at a rate of 1:1,000 Peso Argentino (Neiburg 2006, p. 616).

Despite initial success, the situation deteriorated rapidly as attempts to control prices failed, resulting in a 131.3 percent increase in 1987 (Cortés Conde 2013, p. 281). The situation quickly worsened further, culminating in "prices that increased by nearly 200 percent" by July 1989 (Cortés Conde 2013, p. 285).

The 1990s brought the final currency transformation with the introduction of the Peso Convertible in 1992 at 1:10,000 australes, establishing a fixed 1:1 parity with the U.S. dollar (Table 2). "The key to the system was undoubtedly convertibility, with a fixed exchange rate (one dollar equal to one peso) that worked like the gold standard of the nineteenth century" (Rapoport 2005, p. 64). This system achieved temporary stability but came to a head at the end of 2001, "when the banking and financial system based

on convertibility, whose premise was that the presumed dollarisation of bank deposits via an artificial exchange rate," ultimately collapsed (Rapoport 2005, p. 67).

Throughout this period, "Argentina's median annual inflation was 180 percent from 1975–1990" (Gerchunoff and Llach 2009, p. 419), reflecting the ongoing failure to achieve monetary stability despite four significant currency changes between 1970 and 1992, each representing a dramatic devaluation of the previous currency.

Table 2 summarizes the evolution from the Peso Moneda Nacional (1881–1969), which served as the base currency for decades, through successive currency replacements. The Peso Ley replaced it at a 100:1 ratio, lasting 13 years before the brief Peso Argentino period of just over two years. The Austral followed for six years, achieving a dramatic 1,000:1 conversion rate. Finally, the Peso Convertible emerged in 1992 with an initial 1:1 parity to the U.S. dollar, which persisted until the end of our sample period.

Inflation and Ticket Prices

We measure inflation following the monthly data available in Ferreres (2005). Figure 1 depicts inflation in continuously compounded (log) rates in Argentina between 1943 and 1999. In conventional terms, the average annual inflation rose from around 24 percent between 1943 and 1969 to nearly 140 percent in the 1970s. During the 1980s, inflation kept rising, and by the end of the decade, in December 1989, annual inflation was exceeding 4,900 percent, finally peaking in March 1990 at over 20,000 percent.

[Figure 1 about here]

Attendance figures and gate receipts come from Colussi, Guris, and Kurhy (n.d.), who compiled every Argentina match between 1933 and 1999, including attendance and gate receipts when available. Between 1967 and 1999, our sample period, we have attendance data for 13,264 matches and gate receipts for 14,973. It is, therefore, possible to calculate an implicit ticket price per match by dividing the gate receipts by the attendance figure. Under the inflationary environment described earlier (Figure 1), and given the continuous adjustments in the country's currency, we use Table 2 to obtain a valid time series. Figure 2 presents the results. The blue line depicts the observed nominal prices, which exhibit immense volatility

due to the economy's enormous fluctuations. However, after currency conversion, the price evolution becomes smoother and better reflects what Argentines experienced. Ticket prices rise slightly between 1967 and the early 1970s, then accelerate until the early 1990s, when prices stabilize. This is the series that we take to the data.

[Figure 2 about here]

UNCERTAINTY

As mentioned in the introduction, we proxy macroeconomic uncertainty with the conditional volatility of monthly inflation. Inflation is a natural anchor for household uncertainty in our setting, given that over our sample period, 1967–1999, the price level was arguably the most volatile and least predictable feature of the Argentine macroeconomy. Because monthly inflation ranges from near zero to well over 100 percent, we use the $\ln(1+\pi_t)$ transformation, which compresses the hyperinflationary peaks without distorting the calmer episodes and makes the variance of the series broadly comparable across monetary regimes. Both uncertainty measures described below are constructed from this transformed series at monthly frequency and then merged onto the match-level data, so that each fixture inherits the inflation uncertainty prevailing in the month it was played.

Our primary measure is the conditional standard deviation of inflation from a GARCH model (Engle 1982; Bollerslev 1986). We estimate an autoregressive mean equation with lags up to order three together with a GARCH(1,1) conditional-variance equation, $\sigma_t^2 = \exp(\omega + \delta_1 D_t^H + \delta_2 D_t^C) + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$, where the intercept depends on indicators for the high-inflation (D_t^H, January 1975–March 1991) and *convertibilidad* (D_t^C, April 1991–December 1999) regimes to absorb the pronounced shifts in baseline volatility across the sample. The conditional variance is an ex ante object: at each date it is the variance of that month's inflation implied by information available through the previous month, so its square root measures the predictive uncertainty agents faced in real time rather than the volatility realized after the fact. It follows the conditional-variance construction of inflation uncertainty used by Fountas, Karanasos, and Kim (2006). The estimated dynamics are well behaved, as the α and β coefficients sum to 0.900, within the

stationarity region, implying persistent but mean-reverting volatility with a half-life of roughly 6.6 months.[7] This implies that after six months, half of the uncertainty shock persists. Our GARCH estimate reproduces the volatility clustering that characterizes inflation. Turbulent months follow turbulent months, while inflation remains anchored to a well-defined long-run variance within each regime. The resulting series traces the recognized chronology of Argentine instability, peaking in 1975, 1985, and, above all, the 1989–1990 hyperinflation, before collapsing in the 1990s (Figure 3).

[Figure 3 about here]

As a robustness check, we complement this with a non-parametric measure derived from the Hodrick–Prescott filter (Hodrick and Prescott 1997). The filter decomposes the transformed inflation series into a slowly moving trend and a residual cyclical component by penalizing changes in the trend's growth rate via a smoothing parameter set to the conventional monthly value of 14,400. We take the absolute value of the cyclical component as our measure of short-run uncertainty.[8]

The distinction between GARCH and HP is not one of information direction but of construction. The GARCH variance is one-sided by design: given the estimated parameters, it is built recursively from past innovations alone, so the object at each date reflects only information available at that date. The HP

[7] $\alpha + \beta = 0.90$ which implies that whatever excess turbulence exists above the long-run normal level, around 90 percent of it survives into the next month. The remaining 10 percent dissipates. If each month around 90 percent of the turbulence survives, it follows that after 6.6 months, half the shock will be worn off.

[8] Ravn and Uhlig (2002) argue that the adjustment should follow the fourth power of the frequency ratio rather than the square, which implies a value of 129,600 for monthly data. Their criterion keeps the filter's frequency response approximately invariant across sampling frequencies, and is thus designed to preserve the business-cycle frequencies. Our object is the short-run unpredictability of inflation rather than the business cycle, and the more flexible trend implied by 14,400 allows the trend to absorb the discrete regime shifts that characterize our sample, leaving the cyclical component closer to short-horizon inflation surprises. When using λ =129,600 we obtain a coefficient of −0.042 (still significant at the 5 percent level), similar to the −0.052 reported later in Table 7, and the main discussion remains unaltered.

filter is two-sided, so at any date it is estimated from the full sample, including observations unavailable to contemporaneous agents, and its cyclical component is accordingly a descriptive record of realized variability rather than a forecast of it. This opposition makes the HP measure a demanding robustness check: it is non-parametric, imposes no conditional-variance model, and rests on the reverse informational convention, yet it identifies the same episodes as the most uncertain, and it is correlated with the GARCH series (Figure 3). Agreement between an ex ante model-based forecast and an ex post model-free measure of realized dispersion indicates that our findings reflect the volatility of inflation itself rather than a single parametric specification. Moreover, both imply the same economic mechanism. What matters for household spending is the unpredictability of inflation rather than its level. Anticipated price changes can be planned for; it is the unforeseeable movements in the cost of living that generate the precautionary caution emphasized in the uncertainty literature. Both measures isolate the volatility of inflation rather than its level.

ADDITIONAL DATA

Having described the inflation and price data in detail, Colussi, Guris, and Kurhy's (n.d.) work allows us to develop the additional variables needed to estimate the demand equation properly. Attendance, as already mentioned, is available for 13,264 matches between 1967 and 1999. Table 3, which presents descriptive statistics for these variables, reports a mean attendance of just under 6,900 per game.

At this point, it is necessary to describe how the Argentine league operated over our sample period. Five clubs are considered the "Big Five" in the country: Boca Juniors, Independiente, Racing, River Plate, and San Lorenzo. Presumably, if one of these clubs is involved in the match, the attendance will be larger. As in any other league, derbies are special games, those where the rivalry is significant either for geographic or historical reasons.[9] Although most clubs are from the Buenos Aires area, over the years, a significant

[9] Derbies are all games between the "Big Five," plus some additional games that matter regionally such as Banfield versus Lanús, Rosario versus Newell's, San Lorenzo versus Huracán, Platense versus Atlanta, Chacarita versus Tigre,

number have come from other regions of the country. Thus, using Google Maps, we calculate the distance between the cities of origin for each pair of teams in every match.

The Argentine tournament is tremendously complex during our sample period because it continually adjusts its rules. As an example, we will describe the 1967 competition system, which is not necessarily the most tangled, especially compared to some that took place in the 1980s. Starting in 1967, the league was divided into two tournaments. The first part, denominated *Metropolitano*, consisted of the 20 teams that played the 1966 league plus the two teams promoted from the second division. They divided the 22 teams into two equally sized divisions, with the top six in each division earning the right to play the second tournament of the year, called *Nacional*. Adding to these 12 clubs, four teams from the "interior" of the country, that is, beyond the Buenos Aires area, made the 16 that played the *Nacional*.

Now, the clubs that finished seventh and eighth in each division of the *Metropolitano*, together with another four teams from the interior, played a tournament called *Promocional,* which had no particular prize for the winner. Lastly, the last three clubs of each division of the Metropolitano, plus four teams from the second division, played a *Reclasificatorio*, in which the top six would remain in the first division, and the last four would be relegated.

The top four teams in the *Metropolitano* played semifinals to determine the champion in a grand final. When estimating demand, playing at home naturally makes a difference relative to playing away. The semifinals and final were played in neutral venues, which were very common during our sample period, not only for these decisive stages but also for some teams, that chose to play in larger stadiums, even if not their home stadium, when receiving one of the Big Five at home. The *Nacional* was played as a single round-robin. In 1967, for the first time, there were two champions: Estudiantes won the *Metropolitano*, and Independiente the *Nacional*. Both qualified for the following year's *Copa Libertadores*, South America's top international cup.

Unión versus Colón, Belgrano de Córdoba versus Talleres de Córdoba, Atlético Tucumán versus San Martín de Tucumán and, Gimnasia y Esgrima (Mendoza) versus Independiente Rivadavia (Mendoza).

The structure of the Argentine tournament became so obscure that, at some point, as in 1984, the second-semester tournament (then called the first-division championship) started before the first-semester tournament (called *Nacional)* had finished. That is, the tournament began before a champion was declared. At some point, in the second half of the eighties, there was only one champion per year, but they moved back to two tournaments and champions in the nineties. Over several years, some playoff formats have been used to determine a champion; we control for this using a playoff variable. However, many small-impact additional games occurred beyond the regular season, such as the *Promocional* described for 1967. Those games are controlled for using a non-regular indicator variable. Given the complexity, beyond this general description, explaining the competition rules in detail for every year is beyond the scope of the paper.[10]

[Table 3 about here]

Table 3 presents the summary statistics for the variables described. It also includes a real industrial wage index from Ferreres (2005), which we use as a proxy for income when estimating the demand equation.

EMPIRICAL STRATEGY

We employ the methodology of Coates, Humphreys, and Zhou (2014) and Humphreys and Zhou (2015), who develop a structural econometric approach based on an expected utility model of fan preferences. Fans exhibit a range of preferences regarding attendance, from wishing the home team to win to the well-known uncertainty of outcome hypothesis, but also loss aversion, a preference for quality, and the league-standing effect (Neale 1964). The optimization by fans, subject to ticket prices and income levels, applied to a team's local fanbase, yields an econometric model of the form:

[10] It is, for instance, impossible to use the league standings as a control. The 1967 *Metropolitano* league format serves as an example. It is not possible to compare clubs competing in the *Promocional* (including teams that did not compete in the *Metropolitano's* regular season), those playing for the title, and those trying to avoid relegation.

$$\ln(attendance_{ijt}) = \gamma_0 + [\eta = -1] * \ln(Price) + \gamma_1 \ln(attendance_{ijt-1})$$
$$+ \gamma_2 \ln(Uncertainty_t)$$
$$+\gamma_3 UOH_{ijt} + \gamma_4 \ln(real\ industrial\ wage) + \beta X_{it} + \mu Turmoil_t + FE + \varepsilon_{ijt} (1)$$

Where $attendance_{ijt}$ is the log of the recorded attendance of every match between team *i* and team *j* at time *t*. Persistence in demand is captured by lag attendance, defined as the number of fans who attended the previous home game for team *i*.

Both $Uncertainty$ measures are strongly right-skewed in levels, with the hyperinflation episodes generating values several orders of magnitude above the sample median. To prevent these episodes from dominating the estimates, we take logarithms of both measures. Because the HP measure is an absolute deviation from trend, it approaches zero in tranquil months, and its logarithm would generate extreme negative values. Consequently, we floor it at its first percentile before taking logs. Results are unchanged when the floor is set at the fifth percentile. Finally, we standardize each logged measure using its mean and standard deviation across the months in the estimation sample.[11]

$Turmoil$ controls for whether a dictator was leading the country, for the military regime changes, and a dummy variable for the Malvinas/Falkland war. Dictator is a dummy variable that follows the dates presented in Table 1. The military regime change is a dummy variable taking the value 1 in the month following the change of dictator. However, on some occasions, some interim leaders did not even last a month. The Malvinas/Falkland dummy equals 1 for the period from 2 April 1982 to 14 June 1982. Note that the turmoil variables are potentially confounded with our uncertainty measures. Because the latter is our variable of interest, our empirical model presents five specifications to test the stability of the uncertainty coefficient. The first specification has no turmoil variables. Next, we add each turmoil proxy

[11] The GARCH measure requires no floor, as the conditional standard deviation is bounded away from zero by construction.

individually, and finally include all of them. Getting ahead of our results, the uncertainty coefficient is stable across specifications.

A well-known challenge in estimating a demand equation is the endogeneity of prices (Berry and Haile 2021). In attendance, the problem is compounded by measurement issues. Tickets are not a homogeneous product: clubs sell seats of different quality at different prices, individual transaction prices are unobserved, and only average (implicit) prices are typically available. Noll (2013) shows that this averaging is itself a source of bias, since variation in the composition of cheap and expensive seats affects both the average price and attendance. Nor do the instrumenting strategies available in this literature resolve the problem. Coates and Humphreys (2007) offer the most direct attempt, instrumenting prices with stadium capacity and team-specific time trends in a panel of North American leagues. The difficulty is that, under their pricing model, capacity affects the club's price choice only when the constraint binds. Yet, they report that capacity clearly does not bind in precisely the two leagues, baseball and basketball, where their overidentification tests pass, and that the tests fail in American football, where it may. The team-specific trend fares no better, since it is difficult to exclude a trend from a demand equation in which team popularity itself trends.

Noll's (2013) study on endogeneity in attendance demand models reviews different instrument alternatives for ticket prices in detail. However, in the sport industry, the short-run marginal cost of admitting one more fan is close to zero and nearly invariant across clubs and time. Thus, it cannot play the role that cost shifters ordinarily play in identifying demand. When clubs share the same marginal cost, the price differences observed across matches reflect differences in demand alone, and the price coefficient absorbs whatever the demand covariates leave unexplained rather than measuring the slope of the demand curve. Stadium capacity, the one plausible instrument, enters the pricing decision only when it binds, since it is in any case weak where capacity varies little, thus absorbed by club fixed effects. With only average (implicit) prices available, never per seating category, Noll shows that averaging individual seat prices across qualities effectively forces the price coefficient for each seat type to match a shared coefficient, adjusted by that category's proportion of total seats. As a result, the predicted change in attendance from

the price of a specific seat quality depends on the number of such seats in the venue, not on what ticket buyers actually prefer.[12]

An alternative is the class of instruments proposed by Hausman, Leonard, and Zona (1994), which exploits prices of the same product in other markets. Assuming cost shocks are common across markets while demand shocks are local, prices elsewhere correlate with the price in market *c* but are excluded from its demand equation. The natural analog in our data is the average price charged in other matches on the same matchday. Unsurprisingly, this strategy proved unsatisfactory because the identifying assumption fails in our context, as Berry and Haile (2021) emphasize. Outside perfect competition, prices reflect demand as well as cost, so the exclusion restriction breaks down whenever demand shocks are correlated across markets. In our setting, the correlation is structural, not incidental. Macroeconomic conditions on a given date shift demand for all matches simultaneously, entering the error term directly and entering the instrument through the prices set for other matches.

We therefore follow Noll (2013) and impose the price elasticity rather than estimate it. He argues that when no valid instrument exists, and considering that it is not a variable of interest, an appropriate strategy is to restrict the price coefficient to the value implied by theory. Although much of the sports economics literature estimates demand ignoring price, Noll's (2013) review suggests that even if the estimates are biased, the product is inelastic. Because it is a differentiated, highly inelastic product, we impose the elasticity on a revenue-maximizing club facing near-zero marginal cost.[13] These conditions favor a value at or near 1 in our setting. The marginal cost of selling an additional ticket was close to zero throughout our sample period, and Argentine clubs between 1967 and 1999 earned essentially no additional

[12] Noll argues that a venue's physical layout is an architectural matter unrelated to demand theory. Moreover, the implicit price implies that a match with fewer spectators, mostly concentrated in the low-ticket-price sections, will have both a fall in attendance and a lower average price for reasons beyond demand.

[13] This remains true if clubs, such as those in Argentina, are victory maximizers instead of profit maximizers.

matchday revenue from concessions, parking, or comparable sources. We accordingly constrain the coefficient on the log of price to −1.[14]

To address the UOH, we use two proxies that measure the expectations of the teams playing at time *t*. First, we include an indicator value equal to 1 if the home team won the previous game, and 0 otherwise. Similarly, there is an indicator variable equal to 1 if the away team won the previous game.

Second, we include the average number of points earned by both the home and the away teams over the previous 15 calendar days. To construct this variable, we account for another particularity of the Argentine tournament. In the 1988/89 season, the league changed the point system, awarding three points to the winner instead of two. If a game ended in a draw, they played a penalty shootout, with the winner earning two points and the loser one. Thus, we consider teams to have three points for a win, two for a shootout win after a draw, one for a draw but a shootout loss, and zero for a loss. The system was so messy that they reverted to the traditional two points for a win, one for a draw, and zero for a loss the following season. However, following international trends, starting in the 1995/96 season, it again awarded three points to the winner, zero to the loser, and two for a draw.[15] Moreover, the 15 calendar days include only games within the same tournament because the purpose is to determine fans' expectations for the game relative to that season's performance.[16]

We control for income using the monthly industrial wage and include in the X controls matchday, a dummy variable indicating whether a team is in the Big Five, a dummy variable for whether the game is

[14] The results are robust to alternative measures as shown later.

[15] No penalties, however, for a draw.

[16] The irregular structure of Argentine football runs counter to including Elo ratings. Recall that the competition structure includes double- and single-robin leagues, playoffs that added second-division teams, and multiple qualifiers for an international tournament, to avoid relegation or, simply, to keep competing. In these cases, it is difficult to define home advantage in rating points, while second-division entrants lack a reliable rating. Nevertheless, we ran Elo-controlled specifications in which the coefficients for the variables of interest remained unaltered.

a derby, and the distance between each team's headquarters.[17] It also includes dummy variables indicating whether the game is part of the playoffs (in the sense explained earlier), whether it is a non-regular match as defined earlier, and whether it is a final, semifinal, quarterfinal, or round of 16 match.

[Table 4 about here]

Table 4 shows that the home team accumulated 2.11 points over the two weeks leading up to the current match. The figure for the away team is slightly higher, at 2.26. Not surprisingly, the home team won around 25.5 percent of the games prior to the current match, while the away team won 40.5 percent. This is a consequence of the home bias, which states that teams tend to win more at home than when playing away. Given that teams traditionally play one matchday at home and the following away, the reported means imply that the team playing at home on matchday *t* most likely played away on matchday *t-1*.

Lastly, we include fixed effects for day, home team, away team, and year. Standard errors are clustered by year, since the inflation-based uncertainty measures are common across matches and persist over time, generating serial correlation that year-level clustering absorbs. Given the resulting small number of clusters (33), inference relies on wild cluster bootstrap p-values.[18]

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[17] Matchday is a proxy for the stage of the tournament at any given time. One expects that, as the season progresses, pressure will increase. In traditional round-robin leagues, it is straightforward to understand. In the Argentine case, it can be confusing. Consider the 1967 tournament. On a given date after the regular season, the matchday for all teams is not necessarily the same, and even if it is, they might be playing in another tournament. It is not the same to be playing for relegation, or nothing, as those in the *Promocional*. Still, it remains a proxy for the stage of the tournament.

[18] While the data covers almost all first-division matches played between 1967 and 1999, the uncertainty proxies vary by month and persist from one month to the next. We therefore cluster by year because clustering per month would treat consecutive months as independent when they share much of the same information. This approach follows Abadie et al. (2023), who show that the level of clustering should be set by how the sample is drawn and how the regressor of interest is assigned, not by whether the residuals are correlated. With 33 clusters, t-tests based on cluster-robust standard errors can over-reject; thus, we compute p-values using the restricted wild cluster bootstrap (Cameron, Gelbach, and Miller 2008).

RESULTS

First, we present the results of our main specification based on the GARCH uncertainty measure.[19] Table 5 first reports the coefficients on the control variables across five specifications: one with no dictator, regime change, or war controls; three that add them sequentially; and one that includes all controls, our preferred specification. The stability across specifications is apparent, suggesting the strength of the demand estimation. The estimates closely follow prior expectations. A match involving at least one of the Big Five draws almost three times more attendance, and a derby adds a further 30 percent, both reflecting the significance of the historically dominant clubs and the local rivalry among Argentine fans. The distance between the teams' headquarters has a negative effect, though of negligible magnitude, consistent with many teams from the Buenos Aires area, and, in part, with traveling support being a minor component for much of this period. Matchday is measured backward because of Argentina's intricate, confusing league system. That is, the last game of the season, which is not necessarily the final, is matchday 1. Moreover, some seasons last up to 53 matchdays, others as short as 11. The positive coefficient implies that attendance is higher at the start of the season or that fans may prefer shorter seasons. Having controlled for playoffs and knockout stages, the result implies that, holding everything else constant, fans tend to prefer regular-season matches (or even shorter seasons) when the tournament's organization is less confusing. This remains a hypothesis to be studied, but exploring it in detail is beyond the scope of this paper. The matchday findings, however, do not change the fact that attendance increases as a team advances through the knockout rounds. At the round of 16, attendance is 3.4 times that of an ordinary fixture, 4.4 in the quarterfinals, 4.5

[19] We exclude the Neutral variable because it is not statistically significant and it has no impact on the coefficients of the other variables.

in the semifinals, and the final draws 6.6 times more. Playoffs almost double attendance, while non-regular matches, those played following a regular season that led to nothing, show a 36 percent decrease.[20]

[Table 5 about here]

The expectations proxies behave as the fan-preference framework implies. A home victory in the previous match raises attendance by 14.8 percent, and, notably, an away victory has a nearly identical effect, 15.4 percent. The teams' form leading into a given match matters for both sides: each point the home team accumulates over the previous 15 days raises attendance by 9.1 percent, while away-team form contributes a smaller but precisely estimated 3 percent per point. It follows that fans respond to the anticipated quality of the contest, implying that the match's stakes matter as expected. Finally, the real industrial wage enters positively but is not significant across all specifications, and it does not survive the wild-cluster bootstrap.

Table 6 presents the results from the variables of interest when estimating equation (1). Given that the uncertainty measure is a national monthly series common to all matches, standard errors are clustered by year, leaving only 33 clusters. Conventional cluster-robust inference may be unreliable at that count, so we complement it with wild cluster bootstrap p-values.[21] The table reports these p-values for the uncertainty coefficient at the bottom.[22]

The price elasticity is constrained to minus one in all columns, following the argument developed above. Lagged attendance enters with a coefficient of 0.205, precisely estimated and identical across specifications, indicating meaningful but incomplete habit persistence in match-level attendance.

The central result is the negative, statistically significant coefficient on the GARCH uncertainty measure, even under the bootstrap. Consider the coefficient in column (5) in Table 6. The −0.172 implies

[20] Note that the playoff variable does not include the round of 16 to the final knockout stages. Moreover, over the years, the Argentine league has had various postseason matches that lead to nothing (as in the *Promocional* of the 1967 league). We denominate these games as non-regular matches.

[21] 9,999 replications were done.

[22] We present the wild-cluster bootstrap for the variables of interest.

that a one-standard-deviation increase in log uncertainty reduces attendance by 15.8 percent. This contemporary transitory shock assumes that lagged attendance remains constant, understating the effect of the sustained volatility that characterizes our time period.

Given the dynamic nature of equation (1), we can determine when attendance fully reflects the uncertainty shock by estimating the move from the old to a new steady state: $\gamma_2/(1-\gamma_1) = -0.172/(1-0.205) = -0.216$. It follows that attendance falls by 19.45 percent when the habit to attend clears. Considering a sample mean of just under 6,900 spectators, this amounts to a loss of some 1,342 fans per match.

[Table 6 about here]

Iterating equation (1) forward, it is possible to derive how many weeks it takes for attendance to fully reflect a jump in uncertainty that remains at its new level. To complete the path from an initial steady state, A_0^*, to the new steady state A_1^* we take the lag attendance coefficient, 0.205, from Table 6, and apply the derivation of the path between steady states $\frac{\ln(A_k) - ln(A_0^*)}{\left(\ln(A_1^*) - ln(A_0^*)\right)} = \left(1 - \gamma_1^{k+1}\right)$. The result shows that after the contemporary match ($k = 0$), 79.5 percent of the adjustment to the new steady state is complete. One match later, the shock has covered 95.79 percent, and two matches later, 99.14 percent. With a median of 14 days between a team's consecutive home matches, the habit effect clears within a month of the initial shock, while half of the uncertainty shock remains after 6.6 months.[23]

Lastly, when we sequentially add the Dictator, Regime Change, and Malvinas/Falklands dummies, they are statistically insignificant.

[23] Attendance finishes adjusting within two to four weeks, while half of an uncertainty shock remains after 6.6 months. The −0.216 is therefore not a distant limit the series approaches, but the magnitude that holds once habit has cleared, which happens well before the uncertainty episode is over.

Robustness Checks

An Alternative Uncertainty Proxy

As noted earlier, the Hodrick–Prescott filter derives a cyclical component of realized variability. Because the control variables remain essentially unaltered, with only slight changes in magnitude, we report those results in the Online Appendix (Table A1) and present the main results directly in Table 7.

[Table 7 about here]

The HP uncertainty measure is, as before, negative, implying that economic uncertainty indeed has a negative impact on demand. The contemporary effect implies that a one-standard-deviation increase in log uncertainty, as measured by the HP filter, reduces attendance by 5.1 percent. The habit effect clears, as before, after two home matches, resulting in a 6.34 percent reduction in attendance.

The HP coefficient is about one third of our earlier GARCH estimate. The gap is not surprising. If fans decide to attend based on the uncertainty they perceive, the conditional variance is the relevant object, that is, it measures the expected size of the next inflation surprise given the information available at the time. The absolute HP cyclical component, instead, measures the surprise actually realized, which equals that expectation plus noise. Moreover, because the filter is two-sided, it draws in observations not yet available to fans. The surprise and the two-sided components add variation unrelated to perceived uncertainty and attenuate the coefficient toward zero.

Regarding the Dictator and Regime Change dummies, the results mirror our earlier estimates, as these variables have no statistical impact on attendance. The war dummy is statistically significant using the clustered standard errors, but it does not survive the wild-cluster bootstrap, which yields a p-value of 0.39.

The Role of the Inflation Level

The main finding so far suggests that people stay away from the stadium not because prices are rising, but because they cannot predict what prices will do next. That is, attendance responds to the unpredictability of inflation, not to its level. The two are, however, tightly linked in our sample: the months

when Argentine inflation was highest were, with few exceptions, also the months when it was hardest to forecast (Figure 3). This raises a natural concern. High inflation depresses real purchasing power in the short run, as prices presumably adjust faster than wages, and discretionary spending such as match attendance is a plausible first casualty. If this affordability channel is the true mechanism, our uncertainty measure could inherit its explanatory power simply by proxying for the level of inflation, and the coefficient we have interpreted as precautionary caution would instead reflect households that are poorer in the moment rather than more fearful of the future.

[Table 8 about here]

To separate the two channels, we re-estimate equation (1) including standardized log monthly inflation alongside the uncertainty measure.[24] The exercise asks whether, conditional on the inflation households experienced in a given month, additional unpredictability carries independent explanatory power. Identification stems from episodes in which inflation's level and volatility decouple: the stabilization plans of the mid-1980s and the convertibilidad period feature months of moderate or low realized inflation, accompanied by widely varying degrees of confidence about its persistence.[25] Table 8 reports the results for the variables of interest.[26]

The GARCH–uncertainty coefficient remains significant, pointing in the same direction, though it varies slightly from Table 6's estimates. Lag attendance remains stable, consistent with previous estimates. This implies that our discussion without inflation remains unaltered. The inflation coefficient is negative and survives the wild cluster bootstrap with a p-value of 0.03, indicating that increases in the economy's prices also affect attendance. A one-standard-deviation increase in prices implies a 5.7 percent decrease in contemporary attendance. Relevant, but a fraction of the role of uncertainty. The overall conclusion of this

[24] As before we use the $\ln(1 + \pi_t)$ transformation.

[25] The correlation between the GARCH uncertainty and month inflation from Figure 3 is 0.5, low enough to allow identification.

[26] We report the other variables in Online Appendix Table A2 because they do not vary substantively.

test is that the precautionary interpretation survives conditioning on the level: it is not inflation itself, but the inability to anticipate it, that keeps fans away from the stadium.[27]

Lastly, treating tickets as a differentiated product, we run an alternative version with a price elasticity of −1.1 instead of −1. The results remain unchanged, with precisely estimated GARCH and HP uncertainty coefficients of −0.181 and −0.055, respectively. We therefore do not report the results, which are overall very stable.

DISCUSSION

This paper explores the role of uncertainty beyond macroeconomic aggregates and durable goods. Using a unique match-level dataset for Argentina from 1967–1999, we show that uncertainty has a statistically and economically significant negative impact on a nondurable good. Football attendance is a relevant indicator of a nondurable good because, in Argentina, football is fully embedded in the country's society and culture.

The most significant result, using our preferred specification, is that a one-standard-deviation increase in log uncertainty reduces attendance by 15.8 percent, a nonnegligible figure. Given the model's dynamic nature and fans' habit persistence in attending the stadium, when the uncertainty shock is fully realized, attendance falls by 19.45 percent. This implies that each match played under such conditions loses 1,342 fans. The effect of uncertainty is immediately visible in Figure 4: periods of high uncertainty in the mid-seventies, mid-eighties, and late 1980s and early 1990s had a significant effect on football attendance.

[Figure 4 about here]

Following Figure 4, using the 19.45 percent figure, we can calculate the number of fans that would have attended, had uncertainty not been present. Consider, for instance, the period, not necessarily

[27] We do not replicate the inflation exercise with HP Uncertainty because our preferred estimation follows GARCH, because the main results remain unaltered, and because the correlation between inflation and HP uncertainty is too high (0.84).

continuous, between February 1974 and September 1976, when uncertainty was above one standard deviation and at least 4,718,713 fans attended matches in the Argentine football league.[28] If 4,718,713 fans attended and this figure includes a 19.45 percent fall, then, absent uncertainty, 5,858,117 fans would have attended the football games.

However, during that period, uncertainty was not one standard deviation above the mean but, on average, 1.35 standard deviations. Thus, the impact on attendance was not 19.45 percent but 23.34 percent, implying that between February 1974 and September 1976, while uncertainty was above one standard deviation, clubs should have received 6,130,681 fans instead of the observed 4.7 million.

The negative effect is significant: 1,411,968 fans failed to show up in Argentine stadiums because of economic uncertainty in the mid-1970s. In principle, we could go one step further and calculate how much clubs would have received if those fans had attended. Calculating the implicit price using the gate receipts data and multiplying it by 1,411,968 yields the amount of money foregone by the clubs. However, because high inflation (and hyperinflation) plays a significant role, we would need to normalize prices. Again, this is possible, but combined with currency changes, the figure is eventually less informative than we would like. Thus, we choose to report only the number of attendees who did not go to the stadium due to uncertainty. The figure is massive: 1,411,968/4,718,713 = 29.92 percent of observed attendance.

Between August and October 1985, the average uncertainty rose to 1.38 standard deviations. Replicating the above calculations, the 672,331 fans that, at least, attended league matches should have been 879,976. As before, the figure is relevant: 30.88 percent of observed attendance failed to make it to the stadiums. During the hyperinflation period, between October 1988 and May 1991, the average uncertainty reached 2.01 standard deviations. The 3,055,555 who at least attended during that period should have been 4,518,965. That is a massive 47.89 percent of observed attendance.

Given the design of the econometric model, the impact of uncertainty enters symmetrically in logs, whether the shock is negative or positive. Thus, during the 1990s, the effect runs in the opposite direction

[28] "At least" given that we have attendance data for almost all games, not all.

from the hyperinflation period. Given that uncertainty was significantly lower during the 1990s, attendance benefited. Instead of the 18,034,250 fans that attended between July 1992 and December 1999, when uncertainty was more than one standard deviation below the mean (on average −1.57), the number of fans would have been 13,634,799. That is, just below a third of observed fandom in the stands. Overall, the conclusion is that uncertainty significantly affects households' consumption of nondurable goods, here represented by football attendance.

The robustness exercise on the inflation level connects the results to the literature on the real effects of nominal uncertainty. The hypothesis that high inflation makes future inflation harder to predict and that this unpredictability is itself costly dates back to Friedman (1977). What that literature establishes for economic aggregates, we observe at the level of a single good: households choose whether to consume. Holding constant the inflation they actually faced in a given month, the unpredictability of that inflation still depresses attendance, that is, the uncertainty proxy still depresses attendance by more than the level of inflation itself. It is not what prices did that kept Argentines away from the stadium; it is what prices might do next.

The political variables may surprise. Dictatorship, military regime changes, and the Malvinas/Falklands war are precisely the sort of discrete, datable shocks that the natural-experiment approach to uncertainty exploits, yet none of them enter significantly our demand estimates. It suggests that household consumption is more affected by economic uncertainty than by political turmoil. Although one cannot deny the social impact a dictatorship has on any country, our findings suggest that, day-to-day, whether under a democratic regime or not, consumers feel the economic situation more.

Finally, the setting itself is part of the contribution, as developing economies are structurally more volatile than rich ones. Yet, credible microeconomic evidence on uncertainty comes primarily from stable, high-income settings where variation is muted. Argentina between 1967 and 1999 sits at the opposite extreme of the uncertainty distribution, and the fact that a clean, stable, and theoretically interpretable demand response emerges from hyperinflation, currency reforms, coups, and a war suggests that the precautionary mechanism is not an artifact of the tranquil environments in which it has mostly been studied.

CONCLUSION

This paper explores the role of uncertainty in the consumption of nondurable goods using the case of football attendance in Argentina, an extremely volatile country. The main results suggest that as volatility increases, the impact on households' consumption increases. Indeed, our counterfactual exercises, based on our econometric estimates, imply that during high-volatility periods, relative to observed turnout, attendance falls between 29 and 48 percent, the latter related to the hyperinflation episode of the late 1980s and early 1990s.

A caveat: our uncertainty measures are inflation-based by design. They are appropriate in a sample where the price level was the dominant source of unpredictability, but not a general-purpose index of macroeconomic uncertainty as discussed in much of the literature reviewed. Our main conclusion is that uncertainty does not merely delay consumption, it destroys it, and it does so quickly, through households that can afford the ticket but can no longer plan for it.

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Table 1

MILITARY GOVERNMENTS IN ARGENTINA

Start	End	Military Leader
June 1966	June 1970	General Juan Carlos Onganía
June 1970	March 1971	General Roberto Marcelo Levingston
March 1971	May 1973	General Alejandro Agustín Lanusse
March 1976	March 1981	Lieutenant General Jorge Rafael Videla
March 1981	December 1981	General Roberto Eduardo Viola
December 1981	December 1981	Admiral Carlos Alberto Lacoste (interim)
December 1981	June 1982	General Leopoldo Fortunato Galtieri
June 1982	July 1982	General Alfredo Oscar Saint Jean (interim)
July 1982	December 1983	General Reynaldo Benito Bignone

Table 2

CURRENCY TRANSFORMATIONS IN ARGENTINA

Period	Currency	Exchange Rate vs. U.S. Dollar	Key Events
1881–1969	Peso Moneda Nacional	Variable	Base currency of modern Argentina
1970–1983	Peso Ley	Variable	Introduction: 1 Peso Ley = 100 Pesos Moneda Nacional
1 June 1983–14 June 1985	Peso Argentino	Variable	1 Peso Argentino = 10,000 Pesos Ley
15 June 1985–31 December 1991	Austral	Variable	1 Austral = 1,000 Pesos Argentinos
1 January 1992–1999	Peso Convertible (now just “Peso”)	Initially 1:1 (1992–2001)	1 Peso = 10,000 Australes

Source: See text.

Table 3

SUMMARY STATISTICS

Variable	Mean	Std. Dev.	Min	Max
Attendance	6,899.73	7,240.74	33	69,099
Big 5	0.23	0.42	0	1
Derby	0.06	0.23	0	1
Distance	308.82	357.32	0.00	2,180.00
Round of 16	0.0005	0.0234	0	1
Quarterfinals	0.0035	0.0592	0	1
Semifinal	0.0026	0.0511	0	1
Final	0.0011	0.0342	0	1
Industrial wage (real)	1,513.53	302.80	1,158	2,112.43

Source: See text.

Table 4

SUMMARY STATISTICS: ADDITIONAL CONTROL VARIABLES

Variable	Mean	Std. Dev.	Min	Max
Points Home (15 days within the same tournament)	2.11	1.63	0	10
Points Away (15 days within the same tournament)	2.26	1.64	0	9
Home Victory lag	0.2545	0.4356	0	1
Away Victory lag	0.4056	0.4910	0	1

Source: See text.

Table 5

GARCH UNCERTAINTY: CONTROL VARIABLES

	(1)	(2)	(3)	(4)	(5)
Uncertainty Garch	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
Big 5	1.088***	1.085***	1.090***	1.088***	1.086***
1 if a Big 5 is involved	[0.189]	[0.188]	[0.189]	[0.189]	[0.189]
Derby	0.264***	0.265***	0.264***	0.264***	0.264***
	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]
Distance	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Log (Matchday)	0.200***	0.201***	0.201***	0.200***	0.202***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
	0.138***	0.139***	0.138***	0.138***	0.138***
Home Previous Game Win	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
	0.143***	0.143***	0.143***	0.143***	0.143***
Away Previous Game Win	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
Points Home past 15 days	0.087***	0.087***	0.087***	0.087***	0.087***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Points Away past 15 days	0.030***	0.030***	0.030***	0.030***	0.030***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Round 16	1.229***	1.229***	1.230***	1.228***	1.230***
	[0.040]	[0.040]	[0.041]	[0.040]	[0.041]
Quarterfinals	1.476***	1.477***	1.475***	1.474***	1.475***
	[0.103]	[0.103]	[0.103]	[0.105]	[0.105]
Semifinal	1.505***	1.507***	1.508***	1.504***	1.509***
	[0.162]	[0.161]	[0.161]	[0.162]	[0.161]
Final	1.868***	1.872***	1.879***	1.869***	1.882***
	[0.208]	[0.207]	[0.208]	[0.208]	[0.207]
Playoffs	0.662***	0.663***	0.664***	0.662***	0.664***
	[0.147]	[0.147]	[0.147]	[0.147]	[0.147]
Non-regular match	-0.451***	-0.450***	-0.450***	-0.451***	-0.448***
(see text for definition)	[0.124]	[0.124]	[0.125]	[0.124]	[0.125]
Log Industrial Wage	0.383	0.551*	0.378	0.383	0.542*
	[0.243]	[0.294]	[0.244]	[0.244]	[0.292]
Constant	4.938**	3.756	4.972**	4.943**	3.821*
	[1.928]	[2.233]	[1.934]	[1.932]	[2.222]
Observations	13,133	13,133	13,133	13,133	13,133

Note: Home Team, Away Team, Day of Week and Year FE included in all specifications.

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 6

GARCH UNCERTAINTY: MAIN RESULTS

	(1)	(2)	(3)	(4)	(5)
	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
log Price (η =1)	-1.000	-1.000	-1.000	-1.000	-1.000
log Attendance (lagged)	0.205***	0.205***	0.205***	0.205***	0.205***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
log Uncertainty (Garch)	-0.173***	-0.173***	-0.172***	-0.172***	-0.172***
	[0.061]	[0.061]	[0.061]	[0.061]	[0.062]
Dictator		-0.079			-0.077
(1 if military in power)		[0.085]			[0.083]
Regime Change			-0.059		-0.057
(1 if new military)			[0.041]		[0.038]
Malvinas/Falklands War				0.015	0.016
				[0.032]	[0.032]
Clustered standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1					
	(1)	(2)	(3)	(4)	(5)
Wild cluster bootstrap	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
Bootstrap p-value for Uncertainty	0.001	0.001	0.001	0.001	0.001
Bootstrap CI lo	-0.343	-0.343	-0.343	-0.344	-0.345
Bootstrap CI hi	-0.066	-0.067	-0.065	-0.066	-0.065

Table 7

HP UNCERTAINTY: MAIN RESULTS

	(1)	(2)	(3)	(4)	(5)
	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
log Price (η =1)	-1.000	-1.000	-1.000	-1.000	-1.000
log Attendance (lagged)	0.206***	0.206***	0.206***	0.206***	0.206***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
log Uncertainty (HP)	-0.049**	-0.052**	-0.048**	-0.050**	-0.052**
	[0.021]	[0.020]	[0.021]	[0.020]	[0.021]
Dictator		-0.106			-0.105
(1 if military in power)		[0.103]			[0.099]
Regime Change			-0.064		-0.059
(1 if new military)			[0.045]		[0.040]
Malvinas/Falklands War				0.078**	0.080**
				[0.033]	[0.033]
Clustered standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1					

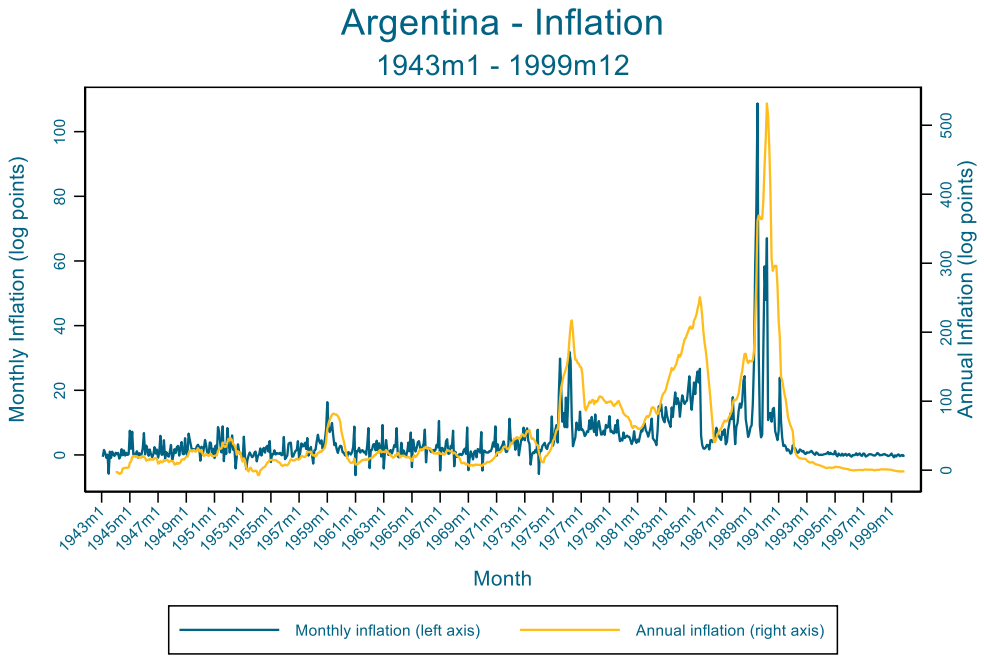
	(1)	(2)	(3)	(4)	(5)
Wild cluster bootstrap	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
Bootstrap p-value for Uncertainty	0.0236	0.0183	0.0326	0.0206	0.0191
Bootstrap CI lo	-0.0867	-0.0896	-0.0859	-0.0875	-0.0890
Bootstrap CI hi	-0.0128	-0.0158	-0.0104	-0.0138	-0.0148

Table 8

GARCH UNCERTAINTY CONTROLLING FOR INFLATION: MAIN RESULTS

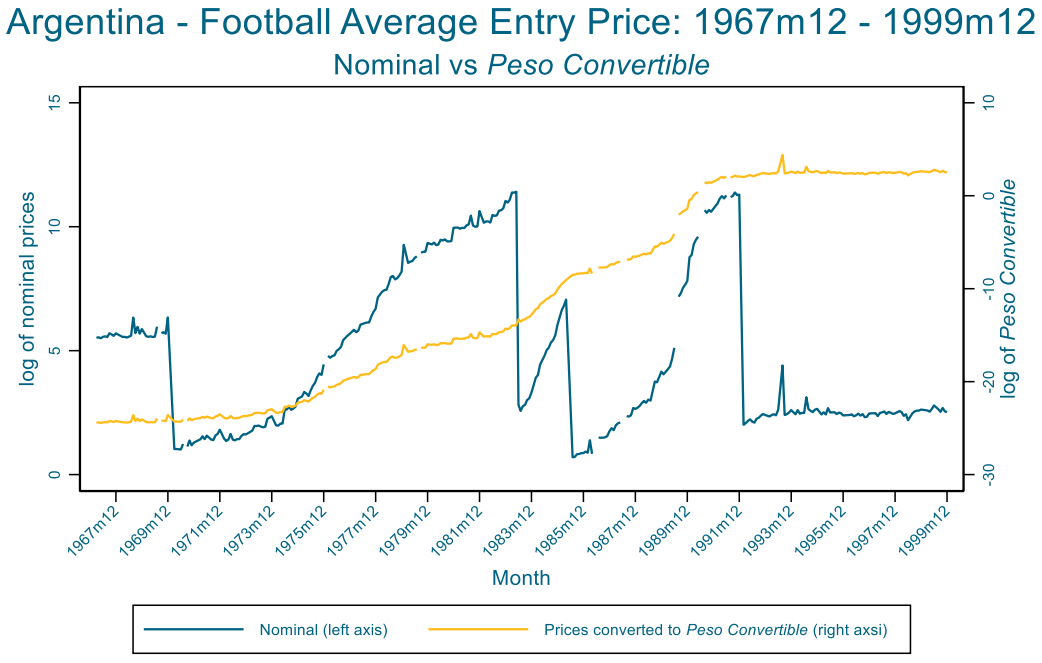
	(1)	(2)	(3)	(4)	(5)
	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
log Price (η =1)	-1	-1	-1	-1	-1
log Attendance (lagged)	0.204***	0.204***	0.204***	0.204***	0.204***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
log Uncertainty (Garch)	-0.158***	-0.158***	-0.157***	-0.158***	-0.157***
	[0.055]	[0.055]	[0.055]	[0.055]	[0.055]
Inflation	-0.057***	-0.059***	-0.057***	-0.057***	-0.059***
	[0.018]	[0.017]	[0.019]	[0.018]	[0.017]
Dictator		-0.114			-0.112
(1 if military in power)		[0.111]			[0.109]
Regime Change			-0.038		-0.034
(1 if new military)			[0.030]		[0.030]
Malvinas/Falklands War				-0.018	-0.018
				[0.030]	[0.029]
Clustered standard errors in brackets					
*** p<0.01, ** p<0.05, * p<0.1					
	(1)	(2)	(3)	(4)	(5)
Wild cluster bootstrap	Only Uncertainty	(1)+ Dictator	(1)+Regime Change	(1) + War	(1)+(2)+(3)+(4)
Bootstrap p-value for Uncertainty	0.0013	0.0013	0.0013	0.0013	0.0013
Bootstrap CI lo	-0.3166	-0.3161	-0.3166	-0.3172	-0.3166
Bootstrap CI hi	-0.0660	-0.0663	-0.0654	-0.0660	-0.0660

Figure 1



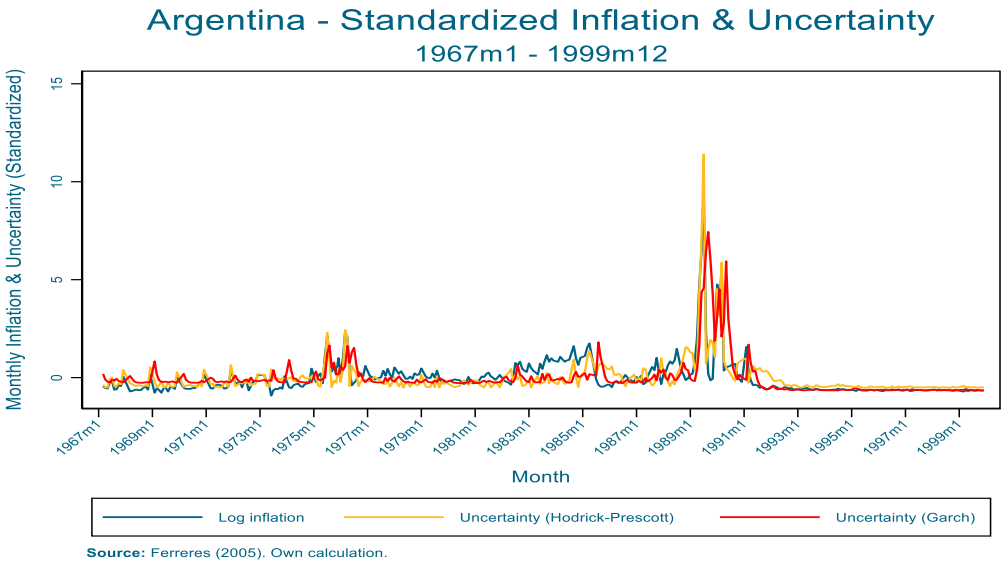
Note: Plotted series are continuously-compounded log rates
Source: Ferreres (2005)

Figure 2



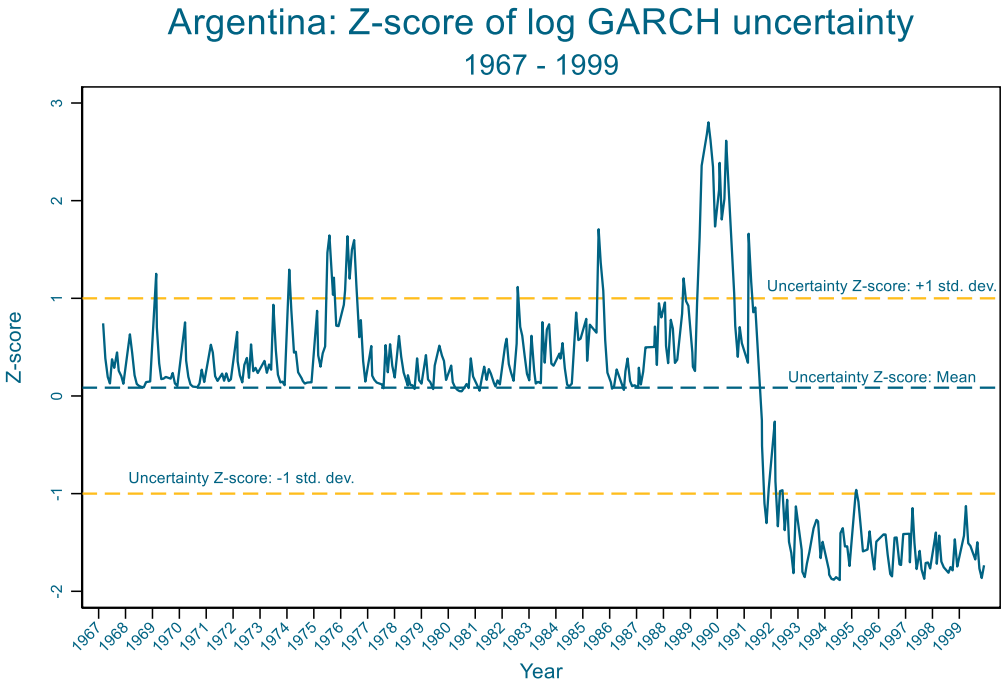
Source: Colussi et al. (NA)
Note: Prices converted to *Peso Convertible* as described in the text

Figure 3



Source: Ferreres (2005). Own calculation.

Figure 4



Source: See text. Own Calculations