Spotlight Personnel: How Hiring and Turnover Drive Service Performance versus Demand

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ABSTRACT

In many sectors of the entertainment industry a few employees are in the public spotlight when performing the key service. For example, in professional team sports a team of players competes in games and in TV shows a cast of artists acts in different episodes. These employees, coined spotlight personnel, are an essential but expensive element of ongoing service delivery. Despite their importance and cost, very little is known about how changes in spotlight personnel affect service performance and demand. To address this gap, this paper uses unique data on professional German soccer teams tracking the quantity (number of players) and quality (average transfer price) of spotlight personnel hiring (incoming transfers) and turnover (outgoing transfers), objective service performance (winning percentage) and demand (ticket sales) across four decades, utilizing both traditional and novel time series methods. The results show that service performance and demand are primarily affected by spotlight personnel hiring rather than turnover. Hiring quantity decreases service performance yet increases demand whereas hiring quality benefits both service performance and demand. The analysis further uncovers that these effects are subject to dynamic interactions and nonlinearities. Investment scenarios showcase how understanding these effects can substantially improve managerial decision making.

Keywords: Service Marketing, Entertainment Services, Sports Marketing, Service Personnel Investments, Spotlight Personnel, Player Transfers, Local Cubic Projections, Impulse Response Functions, Vector Autoregressive Models, Direct Multiperiod Forecasting

Many providers in the entertainment industry,[1] worth $842 billion in the US alone (Statista 2020a, b), rely on a small team of employees to deliver the key service on an ongoing basis. Professional musicians are employed to deliver concerts, actors appear in several seasons of TV shows or theater plays, and sports players compete in a series of games over seasons. We define *spotlight personnel* as the key employees on whom entertainment organizations rely to perform the focal service in the public spotlight during ongoing service delivery. Spotlight personnel are crucial for providers, attested by their dominant role in pushing provider expenditures up to 100% and more of revenues (Ajadi et al. 2020; Rubino-Finn 2016). They are important because they deliver the service and serve as drawing cards for customers.

Entertainment providers have to make hiring and turnover decisions for spotlight personnel. Anecdotal evidence illustrates that these decisions can be very consequential. The soccer team Paris Saint-Germain had mediocre success before its fortunes changed. In 2011 the team was bought by Qatar Sports Investments and used cash injections to hire top players, including Neymar Jr. for a record sum of $250M. The hires have contributed to winning 22 national trophies and to a sixfold increase in ticket demand (Elberse and Vicente 2020). Professional soccer players worth more than $7.35B were traded in 2019 (FIFA 2019).

Despite the relevance of changes in spotlight personnel, there is no systematic research to inform such changes. While management research has studied the role of *frontline* staff hiring and turnover for service performance (Heavey, Holwerda, and Hausknecht 2013; Jiang et al. 2012), *frontline* staff (typically anonymous, low-cost personnel with commonly available talent) are fundamentally different from *spotlight* personnel (typically publicly known, high-cost personnel with scarce talent). Although movie research has pointed to stars' contributions to box

[1] We adopt a broad understanding of the entertainment industry that also includes performing arts and spectator sports (e.g., United States Census Bureau 2017).

office revenues (Carrillat, Legoux, and Hadida 2018; Hofmann et al. 2017), the "*one-off nature*" of movies (Elberse 2007, p. 118) is fundamentally different from the *ongoing* employment of spotlight personnel. The one-off nature of movies makes it difficult to answer questions about *dynamic* effects of *changes* in personnel, questions that arise for ongoing entertainment service delivery (e.g., musicals, theatre shows, TV-Series, sports games; Moon, Bergey, and Iacobucci 2010). Only two studies hint to the role of changes in spotlight personnel. Yang, Shi, and Goldfarb (2009) identify matches between players and sports teams that create the most value and Han and Ravid (2020) show that hiring a star for a Broadway show increases ticket sales.

However, there are three major gaps in the emerging spotlight personnel literature. First, there is incomplete guidance on the service performance and demand implications of changes in spotlight personnel. In balancing service performance and demand entertainment providers face a dilemma as both may require fundamentally different strategies (Ertug and Castellucci 2013). For instance, in the case of a professional sports team, increasing the number of wins often requires materially different decisions than boosting demand (Lewis 2008). Particularly, changes in spotlight personnel disrupt the spotlight personnel team and thus may *harm* service performance. However, changes are necessary to rejuvenate the team and to upskill so they could also *benefit* service performance. Likewise, changes in spotlight personnel could harm customer identification and the anticipation of seeing favored spotlight personnel, thus *reducing* demand. On the other hand, changes may *increase* demand as customers enjoy seeing new faces. Thus, it is not clear how changes in spotlight personnel impact service performance versus demand.

Second, to understand their implications for service performance and demand it is necessary to *disentangle* the changes in spotlight personnel. These changes can be split into hiring and turnover, where we further split *hiring* into the *quantity* and *quality* of human capital added and *turnover* into the *quantity* and *quality* of human capital depleted (Call et al. 2015; Nyberg and Ployhart 2013). While spotlight personnel research has either considered the hiring side only (Yang, Shi, and Goldfarb 2009) or has only focused on the quality of changes in spotlight personnel (Han and Ravid 2020), no prior research has studied the effects of hiring quantity and quality as well as turnover quantity and quality.

The third gap is a lack of research that examines the potentially *dynamic* nature of the effects of changes in spotlight personnel on service performance and demand. Spotlight personnel possess scarce talent and they have to perform interdependent tasks. Leveraging their talent thus is time-intense, calling for a long-term examination of the effects on service performance. Likewise, spotlight personnel are important drawcards for customers, suggesting that there could be long-term effects of changes in spotlight personnel on demand.

To address these gaps, the goal of this study is to examine the impact of changes in spotlight personnel for service performance and demand. We address the following questions: Do changes in spotlight personnel affect service performance and demand in the same or opposite directions? How do *quantity* and *quality* of spotlight personnel *hiring* and *turnover* affect service performance and demand? Are there *long-term consequences* of these changes?

We use comprehensive data from the world's best attended sports league (Collignon and Sultan 2014), the German Bundesliga (soccer), across 40 years for 33 teams to investigate the links between the quantity (number) and quality (average transfer price) of spotlight personnel hires (players joining the team) and turnover (departing players) and two performance variables, service performance captured in objective terms (winning) and demand (ticket sales). We employ a panel data Vector Auto Regressive model with exogeneous variables (VAR-X) to examine the dynamic effects between the variables. We further explore potential dynamic interactions and dynamic nonlinearities by applying Local Cubic Projections (LCP; Jordà 2005), a relatively new, flexible time series model that we introduce to the marketing literature.

A key finding is that hiring is more consequential for service performance and demand than turnover. Another key finding is that hiring quantity *decreases* service performance yet *increases* demand in the short-term (same year) and in the long-term (later years). In contrast, hiring quality *increases* service performance in the short-term and demand in the short- and long-term. The results are robust to different samples, variable operationalizations and time periods.

Local Cubic Projections (LCPs) expand on the VAR-X results. They show that the positive effect of hiring quantity on demand increases if more spotlight personnel were hired recently (a dynamic interaction effect). A double-sized shock in hiring quantity yields a stronger elasticity than a single-sized shock (a dynamic nonlinear effect). Also, the positive long-term effects of hiring quality on service performance and demand increase when recent hires were of lower quality. Finally, the positive long-term elasticity of a single-sized shock in hiring quality on service performance and demand is stronger than the elasticity of a double-sized shock. These additional insights are not available based on the standard VAR-X model.

The paper offers several contributions. First, we provide new insights on the impact of human capital on service marketing outcomes (Hogreve et al. 2017; Kalaignanam et al. 2021; Moorman and Day 2016). We thereby contribute to emerging research about the role of spotlight personnel management for provider performance (Han and Ravid 2020; Yang, Shi, and Goldfarb 2009; see Table 1). Second, this is the first study to measure the performance impact of (i) quantity *and* quality of (ii) hiring *and* turnover of spotlight personnel on (iii) service performance *and* demand. While the focus in the previous literature has been on demand only (Han and Ravid 2020), many entertainment service providers face a dilemma in pursuing service performance and demand as both may imply conflicting approaches to spotlight personnel changes (Ertug and Castellucci 2013; Lewis 2008). Third, the study is the first to consider the *dynamic* (rather than contemporaneous) effects of changes in spotlight personnel on marketing outcomes, including their dynamic interactions and dynamic nonlinearities (Hogreve et al. 2017).

--- Insert Table 1 about here ---

SPOTLIGHT PERSONNEL

Conceptual Background

Marketing studies have highlighted the role of personnel in service and sales (e.g., Hogreve et al. 2017) as well as in top-management positions (e.g., Germann, Ebbes, and Grewal 2015; You et al. 2020). However, little is known about the role of human capital for marketing performance (Kalaignanam et al. 2021; Moorman and Day 2016). There is no systematic research about arguably the most important group of employees for many service providers in the entertainment industry—spotlight personnel. We start by providing a conceptual background to distinguish spotlight personnel from other employees of service providers.

We define *spotlight personnel* as the key employees of entertainment organizations whom they rely on to perform the focal service in the public spotlight during ongoing service delivery. Examples include concerts, performing arts, TV shows and professional team sports such as basketball, baseball, football, or soccer. Figure 1 uses the definition to distinguish spotlight personnel from other personnel by two continuous criteria—involvement in service delivery (high versus low) and focal public attention (high versus low).

--- Insert Figure 1 about here ---

Spotlight personnel (Quadrant 4 in Figure 1) deliver the core service on which providers build their business model, such as playing games for professional team sports. Spotlight personnel are also subject to focal public attention during service delivery. By drawing focal public attention, they shape perceptions of the provider, define the brand, and attract customers.

Frontline staff (Quadrant 2 in Figure 1) are also directly involved in service delivery and include a wide range of service personnel such as customer service and sales representatives (Bendapudi and Leone 2002; Hogreve et al. 2017; Shi et al. 2017). While in many service contexts they are the key service employees (Ployhart, Weekley, and Ramsey 2009; Tremblay 2020), for entertainment experiences frontline staff often vanish in the background as they only complement the core service experience, for instance, by selling drinks and food at sports games. Frontline staff are not subject to focal public attention and hence they are not spotlight personnel.

Enabling staff (Quadrant 1 in Figure 1) such as admin staff or lower and middle management are important to run the business and to build, develop, and support spotlight personnel. While their contributions to firm performance are indirectly accounted for in the marketing capabilities literature (Kalaignanam et al. 2021; Moorman and Day 2016), there is not much research about the role of enabling staff for marketing outcomes. However, they are not the focus of this study. Different from spotlight personnel they are neither directly involved in the provision of the focal service to customers, nor are they subject to focal public attention.

Finally, key decision makers (Quadrant 3 in Figure 1) include top management such as presidents and executives, who make critical strategic decisions (Germann, Ebbes, and Grewal 2015; Moorman and Day 2016; You et al. 2020). Likewise, directors of TV-shows and coaches of top professional sports teams are responsible for key decisions. While top managers, directors and coaches often draw public attention like spotlight personnel, they are usually not involved in the focal service delivery, different from spotlight personnel.

RELEVANT LITERATURE

We now discuss different literature streams that inform our research.

Service and Sales Research

Key insights. Service researchers have argued that frontline staff is key for demand because they perform the service and shape service quality perceptions, customer attitudes and identification with the provider (Heskett et al. 1994; Hogreve et al. 2017). Sales research has also pointed to the role of frontline staff in channeling customer relationships (Bendapudi and Leone 2002), showing that salesperson departures affect demand negatively (Shi et al. 2017).

Relevance for this study. While sales and service research about the effects of human capital on service quality or demand is in an early stage (see also Kalaignanam et al. 2021) and has not studied spotlight personnel, it provides important insights for this study. Some employees are critical for service quality, which eventually increases demand. A recent meta-analysis calls for exploration of the dynamic nature of human capital effects in services, boundary conditions and nonlinearities (Hogreve et al. 2017). We address this call with a focus on spotlight personnel.

Human Resource Management (HRM) Research

Key insights. The HRM literature has studied the role of human capital for firm performance (e.g., Nyberg and Ployhart 2013; Ployhart, Weekley, and Ramsey 2009), defining human capital as employee knowledge, skills, abilities, and other characteristics available to the firm (Crook et al. 2011). One research stream shows that recruitment *procedures* enhance firm performance (Kim and Ployhart 2014; Van Iddekinge et al. 2009) as they improve the quality of the human capital that flows into a firm, enhancing operational performance (Ployhart, van Iddekinge, and McKenzie 2011). Another stream has established a negative effect of staff turnover on firm performance (Park and Shaw 2013). The negative effect is explained by the disruption of the unit structure, unit-specific knowledge, operational routines and social ties caused by the quantity of turnover (Hausknecht, Trevor, and Howard 2009; Kacmar et al. 2006).

Nyberg and Ployhart (2013) argue that recruitment *and* turnover require simultaneous examination because both drive firm performance collectively—but do not provide an empirical analysis. While recruitment research has focused on the *quality* of changes in human capital (Van Iddekinge et al. 2009), turnover research has focused on their *quantity* (Kacmar et al. 2006). Call et al. (2015) argue that both recruitment and turnover have quantity *and* quality aspects, which should be accounted for simultaneously.

Studies in this stream distinguish between two types of performance variables that may be affected by staff changes. *Proximal* performance outcomes relate to operational or objective service performance (Kacmar et al. 2006) or perceived service quality (Hausknecht, Trevor, and Howard 2009). *Distal* performance outcomes capture, for instance, demand (Ployhart, van Iddekinge, and MacKenzie 2011) or profits (Van Iddekinge et al. 2009).

Relevance for this study. HRM research has primarily accounted for frontline staff but has explicitly called for research on changes in human capital with a focus on other employees such as spotlight personnel (Ployhart, van Iddekinge, and MacKenzie 2011). While HRM research has not responded to that call yet, there are several takeaways for our study. One is that changes in human capital should be captured in terms of hiring and turnover and both have quantity and quality aspects. Also, changes in human capital affect proximal (operational service) and distal (demand) performance. While HRM research does not consider that changing personnel may lead to opposite effects for the two performance measures, we argue below that for spotlight personnel changes the consequences for proximal and distal performance measures may differ. And finally, the effects are expected to play out dynamically.

Movie Research

Key insights. Movie research has examined the effect of star participation on box office revenues (Carrillat, Legoux, and Hadida 2018; Hofmann et al. 2017). Movie stars influence demand as they trigger pre-release buzz, or customer anticipation (Karniouchina 2011). Customers hold "parasocial relationships" with movie stars—where they know a lot about movie stars, hold relationship-like feelings and favorable associations, and identify with them but the relationship does not go the other way around (Hennig-Thurau and Houston 2019). Movie stars are also popular among customers (Adler 1985) and function as a quality signal (Rosen 1981).

Relevance for this study. Unlike movie stars who are involved in one-off movie productions, spotlight personnel are contracted to provide *ongoing* service delivery, such as playing dozens of sports games across multiple years. While the one-off nature of movies tends to make it very difficult to study the dynamic effects of new hires or turnover (Moon, Bergey, and Iacobucci 2010),[2] the ongoing nature of the service provided by spotlight personnel allows for studying these effects. Nevertheless, one important take-away from the movie literature for this study is that, like movie actors in general, spotlight personnel are key for the production of an experience good and they draw public attention and demand.

OVERVIEW OF STUDY FRAMEWORK

We adapt definitions of hiring and turnover (Call et al. 2015; Nyberg and Ployhart 2013) to spotlight personnel. We define spotlight personnel *hiring* as the *quantity* and *quality* of human capital that is added to a spotlight personnel team through the addition of new members. Spotlight personnel *turnover* is the *quantity* and *quality* of human capital depletion from a

[2] For an exception, see Elberse (2007) who studies the effects of announcements about star casts on fictional money transactions on HSX, an online movie stock market simulation.

spotlight personnel team through the departure of existing members.[3] We account for the quantity and the quality of spotlight personnel hiring and turnover in four separate variables.

Service providers pursue two key objectives, service performance and demand, albeit with different priorities (Ertug and Castellucci 2013). *Service performance* is the objective service performance of spotlight personnel and reflects the provider's success in delivering the main service promise (Gijsenberg, van Heerde, and Verhoef 2015; Kacmar et al. 2006) such as winning games in professional sports (e.g., Lewis 2008; Meire et al. 2019). Objective service performance is key for customer perceptions of service quality (Gupta and Zeithaml 2006). Second, aggregate *demand* represents the number of customer purchases of the service experience (Lewis 2008). For instance, customers purchase tickets to attend sports games.

Figure 2 depicts the study framework we use to examine the *dynamic* effects of hiring and turnover quantity and quality on service performance and demand. A dynamic effect means that a shock in the independent variable has a short-term (current period) and a long-term effect (following periods) on the dependent variable. While researchers have theorized that changes in human capital affect performance outcomes not only in the short- but also in the long-term (Ployhart, Weekley, and Ramsey 2009), extant research has not studied how spotlight personnel drives provider outcomes dynamically over time.

--- Insert Figure 2 about here ---

FOCAL DYNAMIC EFFECTS

Effects of Changes in Spotlight Personnel on Service Performance

Spotlight personnel hiring quantity → *service performance* (*expectation:* −). The *team*

[3] We consider collective turnover, which includes voluntary and involuntary turnover (see also Heavey, Holwerda, and Hausknecht 2013). This distinction is less meaningful for spotlight personnel as turnover decisions typically result from negotiation between spotlight personnel and provider.

disruption argument postulates that changes in a team cause disruption to established routines and social structures, harming ongoing service performance (Batt and Colvin 2011; Hausknecht, Trevor, and Howard 2009). Disruptions of a team are particularly harmful in settings where individual team members engage in complex interactions to perform an interdependent task (Groysberg, Polzer, and Elfenbein 2006). The performance of spotlight personnel depends on automated routines, e.g., between players in a sports team. The more new spotlight personnel are hired, the more difficult it becomes for the team to develop the routines that allow exploiting the individual skills so that the team becomes more than just the sum of individuals. Consequently, we expect a negative effect of the quantity of spotlight personnel hires on service performance.

Spotlight personnel hiring quality → *service performance* (*expectation:* +). Hiring quality affects the abilities a team can draw from for ongoing service provision. The *team ability argument* is that hiring higher quality personnel increases service performance because it leads to human capital gains (Van Iddekinge et al. 2009), particularly in small teams in which specialized skills combine to the human capital present (Chen and Chung 2021; Tziner and Eden 1985). Spotlight personnel possess highly specialized skills that combine to the overall team ability. For instance, a team of football players in the NFL combines offense and defense specialists. Top-quality spotlight personnel are better equipped to succeed in such demanding, highly specialized tasks. Adding quality members could also lead to critical competitive advantage by motivating other team members to aspire their best and by unlocking synergies (Elberse 2007). We thus expect a positive effect of spotlight personnel hiring quality on service performance.

Spotlight personnel turnover quantity → *service performance* (*expectation:* −). The *team disruption argument* implies that the more spotlight personnel leave, the greater is the disruption of established social structures and routines and the resulting loss in ongoing team performance.

Hence, we expect that the quantity of spotlight personnel turnover reduces service performance.

Spotlight personnel turnover quality → *service performance* (*expectation:* −). The rationale for this effect mirrors the *team ability argument* for the positive effect of hiring quality on service performance. Accordingly, high-quality turnover means that there is a loss in human capital that is critical for the complex task performed by spotlight personnel. Hence, we expect to find a negative effect of spotlight personnel turnover quality on service performance.

Effects of Changes in Spotlight Personnel on Demand

Demand for entertainment benefits from the buzz around the upcoming consumption experience (Karniouchina 2011). The *buzz argument* is that information about novel features of an upcoming entertainment experience fuel customer anticipation, hopes and excitement and thus impacts positively on demand (Houston et al. 2018). Given the public visibility of spotlight personnel and their importance for the entertainment experience, the argument implies that changes in spotlight personnel are of great interest to customers, with implications for demand.

Spotlight personnel hiring quantity → *demand* (*expectation:* +). Research suggests that it matters to customers who is involved in service delivery (Bendapudi and Leone 2006; Decrop and Derbaix 2010). Likewise, we argue that the addition of new spotlight personnel is a matter of great interest to customers who anticipate and hope that the new additions add value and are excited about the prospect of the upcoming entertainment experience. Consequently, we expect that the quantity of spotlight personnel hires increases demand.

Spotlight personnel hiring quality → *demand* (*expectation:* +). The buzz argument further suggests that hiring decisions cause anticipation when the hires are of high quality (Karniouchina 2011), because they are popular (Adler 1985) and signal talent (Rosen 1981). Consequently, we also expect a positive effect of spotlight personnel hiring quality on demand.

Spotlight personnel turnover quantity → *demand* (*expectation:* −). The buzz argument also has implications for the effect of turnover quantity on demand. Since spotlight personnel are a means for customer identification with the provider (Decrop and Derbaix 2010), the more of them are flushed out of the team the greater the loss of identification and the more negative the buzz. We thus expect a negative effect of higher turnover quantity on demand.

Spotlight personnel turnover quality → *demand* (*expectation:* −). We argue that high turnover quality lowers customer anticipation as it means a loss of popularity and signals that the service experience could suffer. This creates negative buzz, leading to a drop of customer anticipation. Hence, we expect a negative effect of turnover quality on demand.

EMPIRICAL CONTEXT

Data Sample

We select professional team sports as the empirical context. We focus on players as they are highly involved in the core service delivery (playing games) during which they attract focal public attention, which identifies them as spotlight personnel. The context allows studying dynamic effects since data on both team service performance (winning) and demand (ticket sales) are publicly available for long time-series. The public nature of the transfer market allows us to measure hiring and turnover quantity (counts) but also their quality in monetary terms.

We study the German professional soccer market. Among the top two growth sports globally (PWC 2019), soccer is the most popular with an estimated 4 billion customers following (Total Sportek 2020). The German *Bundesliga* is the world's best attended professional sports league, selling 45,000 tickets per game on average (Collignon and Sultan 2014). It is representative for many leagues around the globe including the English Premier League (soccer), Spanish Liga ACB (basketball) and Japanese Nippon Professional Baseball. It allows for promotion and relegation between first, second, third and minor leagues. Entry to the first (highest) league has to be earned by moving up through the lower leagues. In each league the teams compete in a home and away round-robin system typically playing 34 matches per season. Points decide which team wins the league. Playoffs are used for promotion and relegation positions only. Seasons start in early August and end in late May. The German professional soccer market is well-suited to study player hiring and turnover because it has a less restricted transfer market compared to U.S. sports leagues that have caps and/or rookie drafting rules. Transfer sums are paid when players are under contract and they are free to move otherwise.

We track 33 teams in the professional *Bundesliga* across four decades for a total of 1,310 team-season observations. We start in the 1979-80 season because the transfer market was negligible before that and we stop in 2018-19 which was the last full season before COVID-19 hit. To avoid panel attrition the sample only includes teams that are currently active in professional soccer. Each of the teams exists for at least thirty years, and they represent 89% of tickets sold in German professional soccer in this period. The sample includes nationally established teams (e.g., Eintracht Frankfurt) and internationally renowned powerhouses (e.g., Borussia Dortmund, the world's best-attended soccer team; Poli, Ravenel, and Besson 2019).

Measures

The focal endogenous variables in the model are spotlight personnel hiring quantity, hiring quality, turnover quantity, turnover quality, service performance, and demand. We capture *hiring quantity* as the number of new players added to a team in a season and *hiring quality* as the average amount spent per new player on the transfer market (Liu et al. 2016; Robert, Marques, and Le Roy 2009). Likewise, we capture *turnover quantity* as the number of players that departed from a team in a season and *turnover quality* as the average euro proceeds per player sold on the transfer market.[4] We measure objective *service performance* as a team's winning percentage, calculated as the percentage of games won in a season (Meire et al. 2019). The second outcome, *demand*, is based on the number of tickets sold for all national league matches in a season (Bloom 1999; Lewis 2008).[5] Similar to other live entertainment providers, the inventory of seats is capped; we therefore divide the number of tickets sold by the number of seats available during the season (Bloom 1999; Lewis 2008). We show in a robustness test that removing the ten observations (0.8%) for which full capacity is reached does not affect the results. We adjust all monetary measures for inflation using the German Consumer Price Index. We use log variables to reduce skewness and to facilitate the interpretation of the effect sizes as elasticities (e.g., Trusov, Bucklin, and Pauwels 2009).

We include exogenous variables in the model. Team fixed effects account for unobserved team characteristics. We capture team age through the log of the number of seasons since a team entered professional soccer (Brown and Lattin 1994). We include a step dummy variable for the introduction of the third professional league in 2008-09. As playing in different leagues may have consequences for demand as well as for hiring and turnover (higher leagues are considered more attractive), we use five dummies for the league the team plays in. We use a step dummy to account for the joint occurrence of the Bosman ruling on transfers in the EU and the introduction of the three-point system in the 1995-96 season; a step dummy for the integration of East Germany's soccer clubs after German reunification in the 1991-1992 season and a step dummy

[4] We note that the transfer market valuations reflect a subjective, negotiated quality rather than objective quality; at times players may be under- or overvalued relative to their unobserved objective quality. Also, while most new players will see the pitch, we do not require new players to play games to be included in our measures.

[5] Other demand indicators include sales of TV rights, merchandising, and sponsorship contracts. Limited data availability precludes us from using them, yet teams that do well in terms of ticket demand also do well in terms of these other indicators (Yang, Shi, and Goldfarb 2009). We find a correlation of .69 between ticket sales and overall revenue (N=213) and a correlation of .59 between ticket sales and media rights (N = 67) in subsamples for which these data are available. Hence, we expect similar insights for these other indicators as for ticket demand.

for the effects associated with the Euro introduction in 2002. We include dummies for whether the German national team won an international title before the season. Finally, we control for the population of each team's hometown.[6] Table 2 provides an overview of the data and measures.

--- Insert Table 2 about here ---

Descriptive Statistics

Table 3 offers descriptive statistics and correlations. Teams sell tickets for 51.95% of their seat capacity on average per season and they win 40.22% of their games. The quantity of newly hired players per season (10.28) approximately matches the number of players departing (10.37), noting that typical squads consist of 25-30 players. Hiring quality (average transfer spend per player) is higher than turnover quality (average transfer income): €531k versus €374k. A reason for the difference is that some players retire from professional soccer each season and thus can no longer be sold to another team. Another reason is that teams in financial distress sell players for less than they have paid. The standard deviations of both metrics (€1,439k for hiring quality and €1,041k for turnover quality) show that these amounts are highly variable. For instance, teams like Borussia Dortmund invest more than €12 million on average per player, while others such as Eintracht Braunschweig or MSV Duisburg spend approximately €300k.

--- Insert Table 3 and Figure 3 about here ---

Time series plots. Figure 3 illustrates the time series history of the key metrics hiring quantity and quality, turnover quantity and quality, service performance, and demand for three prototypical teams. The figure shows a variety of patterns, underlining the richness of the dataset.

MODELING APPROACH

[6] Wealth of team ownership may also be a relevant factor. Data on team wealth are not available (and in Germany, soccer clubs are at least for 51% owned by supporters). However, wealth of team ownership is indirectly reflected in the model through past hiring activities and past performance as well as team fixed effects.

To model the dynamic effects between changes in spotlight personnel, service performance and demand, we estimate a panel data Vector Auto Regressive model with exogeneous variables (VAR-X)—the workhorse model to assess dynamic relationships between multiple time series in marketing (e.g., Dekimpe and Hanssens 1999).

Unit Root Tests. We use panel-data unit root tests, including Fisher ADF, Fisher PP, Im, Pesaran and Shin W-stat, Levin, Lin and Chu t*, and Breitung t-stat (Breitung 2000; Im, Pesaran, and Shin 2003; Levin, Lin, and Chu 2002). Across all tests, we find that all six endogenous variables are mean and trend stationary at $p < .01$. For the VAR-X model specification, we use a lag length of 1 as determined via the Bayesian Information Criterion (BIC) (Schwarz 1978).[7]

VAR-X model. The endogenous variables are $\ln Demand_{it}$, $\ln ServicePerformance_{it}$, $\ln HiringQuantity_{it}$, $\ln HiringQuality_{it}$, $\ln TurnoverQuantity_{it}$, $\ln TurnoverQuality_{it}$, observed over teams i=1,…,n and time periods (years) t=1,…,T. We stack these six endogenous variables into a 6×1 vector $\boldsymbol{y_{it}}$, modeled as:

(1) $$\boldsymbol{y_{it}} = \boldsymbol{\alpha_i} + \boldsymbol{\Phi_1}\, \boldsymbol{y_{it-1}} + \boldsymbol{\Gamma x_{it}} + \boldsymbol{v}_{it},$$

where $\boldsymbol{y_{it}} = \begin{pmatrix} \ln Demand_{it} \\ \ln ServicePerformance_{it} \\ \ln HiringQuantity_{it} \\ \ln HiringQuality_{it} \\ \ln TurnoverQuantity_{it} \\ \ln TurnoverQuality_{it} \end{pmatrix}$, $\boldsymbol{\alpha_i}$ is a 6×1 vector of team fixed effects, $\boldsymbol{\Phi_1}$ is a 6×6 matrix of coefficients, $\boldsymbol{x_{it}}$ is a K × 1 vector of K independent variables, $\boldsymbol{\Gamma}$ is a $6 \times K$ matrix of coefficients and $\boldsymbol{v}_{it}$ is a 6×1 vector of error terms with mean zero and a 6×6 covariance matrix $\boldsymbol{\Sigma}$ (e.g., Pesaran and Shin 1998). For $\boldsymbol{x_{it}}$ we use the exogeneous variables

[7] In time-series modeling the BIC is a commonly used method to determine lag length (see also Colicev et al. 2018, Hewett et al. 2016, Gijsenberg et al, 2015). The BIC has been found to be the most accurate criterion for all realistic sample sizes (Ivanov and Kilian, 2005) and it asymptotically approximates the marginal density of the data which is used to construct the Bayes factor in Bayesian hypothesis testing (Allenby, Arora and Ginter, 1998).

discussed above. Estimated coefficients are reported in Web Appendix A. To check whether the exogenous variables capture the major exogenous changes in the data, we test for structural breaks in the aggregate residuals (Bai and Perron 2003). Since we find no statistical evidence (p>.1) for breaks, we do not expand the set of exogeneous variables. The VAR satisfies the stability condition with the largest eigenvalue equal to .529 and no roots outside the unit circle.

In VAR models it is infeasible to interpret estimated coefficients directly (Sims 1980). Instead, the individual coefficients of $\boldsymbol{\Phi_1}$ (or their significance) are used to calculate impulse response functions after the VAR has been estimated (e.g., Trusov, Bucklin, and Pauwels 2009). The key notion of an IRF is that there is an unexpected windfall (or shortfall) in one or more of the endogenous variables and the IRF shows how its effect on the endogenous variables unfolds over time. To illustrate the existence of such shocks in our empirical (soccer) context, we observe that teams experience major temporary windfalls, e.g., as a result of qualifying for the Champions League but also temporary shortfalls due to, e.g., the COVID-19 pandemic (estimated loss of more than \$7B for Europe's major soccer leagues; Lane 2021), UEFA fines for fan misbehavior or termination fees for fired managers. An impulse response function is the difference between two forecasts, one with a shock in the error term at time t ($\boldsymbol{v}_{it} = \boldsymbol{d} = (d_{1it}, d_{2it}, d_{3it}, d_{4it}, d_{5it}, d_{6it})'$) and one without such a shock ($\boldsymbol{v}_{it} = \boldsymbol{0} = (0,0,0,0,0,0)'$). The IRF for period s is calculated by assessing how the shock in the error term at time t propagates to time t+1, which then carries over to time t+2, etcetera, until period s (Pesaran and Shin 1998):

(2) $IRF_{VAR}(t, s, \boldsymbol{d}) = \boldsymbol{\Phi}_{\boldsymbol{1}}^{s}\boldsymbol{d}$ where $\boldsymbol{\Phi}_{\boldsymbol{1}}^{s} = \boldsymbol{\Phi_1} \cdot \boldsymbol{\Phi_1} \cdot \ldots \cdot \boldsymbol{\Phi_1}$ (product of s matrices).[8]

RESULTS

[8] This IRF expression for a VAR model with one lag shows that it is a linear function of the shock d. The same linearity assumption applies for generalized IRFs for a VAR with more than one lag (Pesaran and Shin 1998, Eq. 4).

We report generalized IRFs (GIRFs) that capture the contemporaneous and dynamic impact of shocks (e.g., the effect of a +/-1SD unexpected shock of hiring quantity on demand, accounting for the error correlation with the other endogenous variables); see also Dekimpe and Hanssens (1999). We report the GIRFs for all (6 × 6 =) 36 effects between the endogenous variables in Web Appendix B. GIRFs show the change in the log of variable *Y1* ($\Delta lnY1$) in response to a 1SD shock to the log of another variable *Y2* ($\Delta lnY2$). Due to the expression in logs, $\Delta lnY1$ equals the percentage change in *Y1* that results from a $\Delta lnY2$ percentage change in *Y2*. In line with the market response tradition (e.g., Trusov, Bucklin, and Pauwels 2009), Figure 4 reports the GIRF results for the focal dynamic relationships as arc elasticities to facilitate their interpretation, $\mu_{arc}(=\Delta lnY1/\Delta lnY2)$. While the elasticities may seem tiny, the effect sizes are far from negligible when translated into real-world numbers as we demonstrate in a separate section below. We denote effects in the same year (year 0) as short-term effects and label effects in any later years (year 1, 2, etc.) long-term effects.

--- Insert Figure 4 about here ---

Effects of Changes in Spotlight Personnel on Service Performance

Quantity & Quality of spotlight personnel hiring → service performance. We find the expected negative significant short-term effect of hiring *quantity* on service performance. Figure 4a shows that a 1% increase in hiring *quantity* is associated with a significant .08% short-term decrease in service performance, becoming insignificant after that. Thus, when a team increases the number of new hires by 1%, the fraction of games that are won in a season goes down by .08%. Hiring *quality* has a positive significant short-term effect on service performance, as expected. A 1% increase in hiring quality (spend per new player) significantly increases service performance by .01% in the long term (Fig. 4b).

Quantity & Quality of spotlight personnel turnover → service performance. Although we expected negative effects, we find no significant effect of turnover *quantity* or turnover *quality* on service performance (Fig. 4c, 4d).

Effects of Changes in Spotlight Personnel on Demand

Quantity & Quality of spotlight personnel hiring → demand. While Figure 4e shows that hiring *quantity* does not affect demand in the short-term, we find a significant (as expected) positive long-term effect that peaks in year 1, where a 1% increase in hiring quantity increases demand by .09%. Thus, hiring 1% more players increases capacity utilization rate by .09%. The long-term effect gets weaker over time but remains significant. As expected, we find a significant positive short-term effect (but no long-term effects) of hiring *quality* on demand. A 1% increase in hiring quality increases short-term demand by .01% (Fig. 4f).

Quantity & Quality of spotlight personnel turnover → demand. The results provide no significant evidence for the expected negative effect of turnover *quantity* on demand (Fig. 4g). We do find that a 1% increase in turnover *quality* is associated with the expected short term decrease in demand (by .01%), and that it also decreases demand in the long term (Fig. 4h).

Additional Tests

We assess the stability of the findings through a series of robustness tests. We run VAR-X models using different sampling periods, team samples, and demand measures. Specifically, we estimate the model for six sampling periods varying in start and end year by +/- 2 and +/-5 years (i.e., 1975-2019, 1978-2019, 1982-2019, 1985-2019, 1980-2017, 1980-2014). Amongst others, these sampling periods account for the impact of major external shocks such as the first player transfer over 1 million Euro in 1978 (transfer of Kevin Keegan to Hamburger SV), the take-off of media rights in 1985, or the introduction of the 2nd Bundesliga in 1985. We further run VAR-X models for two samples with a reduced number of teams to test for the potential impact of outliers—excluding the two best performing teams (i.e., Bayern Munich and Borussia Dortmund) and excluding the two worst performing teams (SpVgg Greuther Fuerth and SpVgg Unterhaching). We consider alternative measures of hiring and turnover quality, using the maximum euro amount a team spent/earned for a single new/departed player. We add two additional endogenous variables capturing the concentration of transfer sums from hiring or selling players because the distribution of these sums could make a difference. We replace the demand measure by the log number of tickets a team sold for national league matches. Finally, we re-estimate the model for a sample excluding the ten observations (.8% of the sample), where stadium capacity was fully utilized. Correlations between the IRFs resulting from the robustness checks and those of the main model are high (mean correlation = .985), confirming the robustness of our findings (Web Appendix, Table C.1).[9]

The study framework implies that the focal effects of hiring and turnover on demand could be mediated by service performance. The evidence offered in Web Appendix D suggests that the demand effects of hiring quantity and hiring quality are partially mediated by service performance, and that turnover quality has a direct negative impact on demand.

Summary and Discussion of Key Findings

Spotlight personnel hiring is more consequential than spotlight personnel turnover. We find that all four of the expected effects of hiring on service performance and demand are significant but only one of the four turnover effects is significant. A possible explanation is that managers deliberately focus turnover decisions on those spotlight personnel whose departure is less likely to materially harm service performance and demand. For instance, players who did not

[9] A potential concern is that a team hires more expensive players anticipating higher demand. This scenario is quite unlikely given the much earlier timing of transfers (before the season) compared to demand (during the season).

often feature in the base squad could be more likely to be sold, with limited adverse effects on the team's performance or on spectator interest.

The service performance-versus-demand-dilemma. Researchers have long debated the dilemma entertainment providers face when pursuing both service performance and demand (Ertug and Castellucci 2013; Lewis 2008). In terms of changes in spotlight personnel, this dilemma becomes evident in the results. We find contrary effects of hiring quantity on service performance and demand. While adding many new spotlight personnel reduces service performance, it increases demand. Interestingly, the same conflict does not play a role for hiring quality, which is rewarded both in terms of service performance and demand.

Dynamic effects. The results show that changes in spotlight personnel have short- and long-term effects on service performance and demand and that these variables themselves also impact each other's trajectory (see Web Appendix B). Figure 4 thereby suggests that not accounting for these dynamic effects would substantially underestimate the actual effects.

EXPLORING DYNAMIC INTERACTIONS AND DYNAMIC NONLINEARITIES

Flexible Effects in the Focal Dynamic Relationships

Since the VAR-X results indicate that hiring (rather than turnover) decisions are most consequential, we further explore their impact on service performance and demand. Since spotlight personnel has to be embedded in an existing team, it is reasonable to expect that the impact of new hires depends on the hiring history, i.e., the quantity and quality of hires added last season. This points to potential dynamic interaction effects where the effect of a shock (e.g., in hiring quantity or quality) depends on the hiring history, i.e., the quantity and quality of hires added last season. Likewise, the marginal impact of additional new hires in a season likely depends on the quantity and quality of other hires made this season, pointing to potential dynamic nonlinear effects. By exploring these flexible dynamic interactions and nonlinearities, we address recent calls for more flexible empirical examinations of the link between human capital and firm performance (Hogreve et al. 2017; Park and Shaw 2013). While one can argue for manifold dynamic interactions and nonlinearities in the effects of hiring quantity and quality on service performance and demand, there is no clear theoretical foundation to direct such arguments. Hence, we do not formulate ex ante expectations. Instead, we explore whether these relationships play a role and offer post hoc arguments to substantiate the discoveries.

Local Cubic Projections

Motivation. The exploration goal calls for a method that flexibly accounts for dynamic interactions and nonlinearities in the focal dynamic effects. While the VAR-X model used so far offers insight in the focal dynamic effects, it assumes the absence of dynamic interactions and nonlinearities. The VAR-X based IRFs (equation 2) assume that the effect of a shock does not depend on the past values of the endogenous variable (no interaction effects) and that the effects are linear (proportional to the shock size). Accounting for them in a VAR-X model requires the formulation of case-specific extensions and functional forms, all of which have to be identified a priori (e.g., Gijsenberg, van Heerde, and Verhoef 2015; Luo, Raithel, and Wiles 2013). This is empirically challenging (Pauwels and Srinivasan 2004) and very hard when the phenomena under investigation are not yet sufficiently founded in theory (Lehmann 2020)—as in this study. Rather than expanding the VAR-X model with (ad hoc) interactions and nonlinearities, we need a model that allows for flexible exploration of dynamic interactions and nonlinearities.[10]

We apply local cubic projections (Jordà 2005) to flexibly accommodate dynamic effects.

[10] Log variables account for a restricted functional nonlinear form (a positive effect stays positive, a negative effect negative). Quadratic and cubic functions capture other nonlinear functional forms, allowing effects to change directions parabolically (e.g., from positive to negative and back).

As Jordà (2005) points out—unlike a VAR model—local *cubic* projections accommodate *dynamic interaction effects* (the dynamic effect of one variable on another depends on the history of the same or other variables) and *dynamic nonlinear effects* (the dynamic effect is not proportional to the size of the shock) without identifying them a priori. LCPs also account for dynamic asymmetric effects, yet they are not the focus of this study.[11] To the best of our knowledge, this is the first study in marketing to use LCPs. We thus offer a more detailed introduction to local (cubic) projections in Web Appendix E.

Model Specification. Local Cubic Projections (LCPs) operate fundamentally differently from VARs. Whereas VARs obtain the impulse response for *s* periods ahead by repeatedly multiplying the shock by the matrix with autoregressive parameters (e.g., see equation 2), LCPs regress the endogenous variable at *s* periods ahead on linear, quadratic and cubic terms which translates into the following estimation equation *for each horizon s*:

$$\text{(3)} \qquad \boldsymbol{y_{it+s}} = \boldsymbol{\alpha_{is}} + \boldsymbol{B_{s+1}}\,\boldsymbol{y_{it-1}} + \boldsymbol{Q_{s+1}}\,\boldsymbol{y^{2}_{it-1}} + \boldsymbol{C_{s+1}}\boldsymbol{y^{3}_{it-1}} + \boldsymbol{\Gamma_s x_{it+s}} + \boldsymbol{v_{LCP,i,s,t}}.$$

For the LCP, the IRF for an *s*-step ahead forecast can then be calculated as (Jordà 2005):

$$\text{(4)} \qquad IRF_{LCP}(t,s,\boldsymbol{d}) = \boldsymbol{B_s\,d} + \boldsymbol{Q_s}\left(\boldsymbol{2}\cdot\,\boldsymbol{y_{it-1}}{\circ}\boldsymbol{d} + \boldsymbol{d^2}\right) + \boldsymbol{C_s}\left(\boldsymbol{3}\cdot\,\boldsymbol{y^{2}_{it-1}}{\circ}\boldsymbol{d} + \boldsymbol{3}\cdot\,\boldsymbol{y_{it-1}}{\circ}\boldsymbol{d^2} + \boldsymbol{d^3}\right),$$

where °, ^{2}, and ^{3}, are the Hadamard (element-by-element) vector products, squares and cubes.[12]

The key difference between the IRF for the VAR in (2) versus the LCP in (4) is that, while the VAR only estimates one equation to obtain *iterated forecasts* for all horizons, the LCP approach uses a collection of regressions, i.e., *direct forecasts,* one for each horizon. Unlike VAR models where the stability of the iterated forecast depends on the estimates of

[11] We account for asymmetric effects by separating spotlight personnel inflows (hiring) from outflows (turnover). The literature about the link between human capital and firm performance does not point to further asymmetries.
[12] In line with other papers that use Local Projections (e.g., Jordà 2005; Li, Plagborg-Møller and Wolf 2021), we use the optimal lag length as determined by the BIC for the VAR-X to select the lag length for the LCP (i.e., one lag).

autoregressive parameters (requiring unit root tests), LCPs do not use iterated forecasts but rather base the IRF directly on the autoregressive parameters ($\boldsymbol{B}_{s+1}, \boldsymbol{Q}_{s+1}, \boldsymbol{C}_{s+1}$) relevant to forecast horizon s. Hence unlike VARs that require *stability* tests —which in the context of linear systems such as VARs are often termed stationarity tests as stability implies stationarity (see Lütkepohl 2005, p. 25)— there is no need for *stability* tests for LCP's *nonlinear* dynamic structure.

The quadratic and cubic terms in (3) do not have substantive meaning, but they allow the *s*-period forecast at period *t* for the IRF_{LCP} to depend on values of the endogenous variables stacked in vector $\boldsymbol{y}$ in period *t-1*, as can be seen in (4). Unlike the history independent VAR-X estimates, this creates path or history dependence and readily accounts for dynamic interaction effects, where the effects of any one variable are allowed to depend on the history of any other variable in the model. For instance, the model allows the dynamic effect of a change in one variable (e.g., hiring quantity) to depend on its own history (lagged hiring quantity) or the history of any other variable (e.g., lagged hiring quality). The quadratic ($\boldsymbol{d}^2$) and cubic ($\boldsymbol{d}^3$) terms in (4) also allow for nonlinearity: a *k*-times sized unit shock is no longer restricted to entail a *k*-times sized effect.

Importantly, no matter the number of lags in a VARX model, its IRFs are still a linear function of the shock size d (see footnote 8). In contrast, due to the cubic and quadratic terms, LCP-based IRFs (even with just one lag) are more flexible and allow for interactions and nonlinearity. Allowing for more lags in a VAR model would probably decrease the difference between VAR-based versus LCP-based IRFs because the VAR becomes more flexible as the number of lags increases. However, the difference will not disappear because LCPs have the cubic and quadratic terms that cannot be captured by a linear VAR. [13]

[13] Similar to LCPs, machine learning (ML) is also based on a nonlinear function to link a dependent variable to independent variables. However, a key difference is that the primary goal of ML is prediction of the dependent

Results from Local Cubic Projections

We calculate the impact of a GIRF-sized shocks (e.g., Dekimpe and Hanssens 1999) using Jordà's (2005) method that allows to calculate the impact of any shock. We calculate analytical standard errors for the IRFs in line with Jordà (2005) (Web Appendix E) and translate the effects into arc elasticities using the same expression as for VAR-X.

While Web Appendix F reports all LCP parameter estimates, Web Appendix G shows the LCP-IRFs for all (6 × 6 =) 36 effects between the endogenous variables. It also reports the IRFs for local linear projections (LLP), which is a nested version of LCP that omits the quadratic and cubic terms contained in equation (3). Albeit with some minor differences in the exact years for which we find significant effects, the results for the LLPs and the LCPs confirm the results from the VAR-X models in terms of direction, significance and magnitude. Web Appendix C offers the same robustness tests performed for the VAR for the LLP (Table C.2) and the LCP (Table C.3). Web Appendix H reports a holdout sample comparison that shows that the LCP predicts better than the VAR-X and the LLP.

The focus in this section is on the exploration of dynamic interactions and nonlinearities, which are flexibly accommodated by LCPs (Figures 5-7). To identify years in which dynamic interaction effects and nonlinear effects are present, we have to test whether they are significant. We therefore calculate the differences of the IRFs and their associated analytical standard errors (see Web Appendix E). A dynamic interaction or nonlinear effect exists if the difference between the relevant IRFs is significantly different from 0 ($p < .05$).

--- Insert Figures 5-7 about here ---

As mentioned before, we focus the exploration on the effects of hiring quantity and

variable whereas the key goal of LCP is substantive insight, namely isolating the dynamic effect of a shock in an independent variable on the dependent variable.

quality both for service performance and demand because the hiring effects are more consequential than the turnover effects. However, note that the LCP also accounts for potential dynamic interactions and nonlinearities with respect to all other focal effects in the model. For instance, it accounts for dynamic interactions between turnover quality and quantity. The LCP exploration yields the following substantive insights beyond the VAR-X findings.

Hiring quantity has a uniform negative effect on service performance. We find no significant dynamic interaction or nonlinearity for the effect of hiring quantity on service performance (Web Appendix I). Irrespective of the history of the endogenous variables and the shock size, hiring quantity has a negative effect on service performance, in line with the disruption argument.

For service performance, hiring quality is more beneficial if used sparingly. We find significant dynamic interactions in the effect of the quality of spotlight personnel hiring on service performance (Figures 5a-5c). When lagged hiring quality is low (-1SD; Fig. 5b), the long-term effects of hiring quality on service performance are significant and positive. When lagged hiring quality is high (+1SD; Fig. 5a), we find no significant long-term effects. The difference is significant in the long term (Fig. 5c). Thus, hiring quality pays off in terms of service performance but the effect is weaker if high quality personnel was added last year.

We also find a dynamic nonlinearity. The arc elasticity of a double-sized shock (+2SD; Fig. 5e) in the long term is significantly smaller than the arc elasticity of a single-sized shock (+1 SD; Fig. 5d). This difference is depicted in Figure 5f. Thus, the marginal service performance effect of hiring quality becomes weaker as more quality is hired.

These findings are in line with the team ability argument. Initially, high hiring quality (this year or last) alleviates the most pressing quality shortcomings, limiting the contribution of additional quality hires. This argument is consistent with Chen and Chung (2021), who find that sales teams benefit the most from high quality members when they are the exception in the team.

For demand, hiring quantity is good and more is even better. We find a significant dynamic interaction in the effect of spotlight personnel hiring quantity on demand. There is a positive long-term effect of hiring quantity on demand when lagged hiring quantity is high (Fig. 6a), but no significant effect when lagged hiring quantity is low (Fig. 6b). The difference is significant in the long term (Fig. 6c). Thus, additional hires have an even stronger effect on demand when there were above-average new hires last year.

We also find a dynamic nonlinearity. The arc elasticity of a double-sized shock (Fig. 6e) is higher than the arc elasticity of a single-sized shock (Fig. 6d), and it is longer-term in nature compared to the single-sized shock. Figure 6f illustrates that the difference is significant in the long-term. Thus, the marginal demand effect of hiring quantity becomes stronger as more quantity is hired in the same year.

The VAR-X findings point to a significant positive effect of hiring quantity on demand, in line with the buzz argument. The significant dynamic interaction and nonlinear effects from the LCP show that even more hires attract disproportionately more demand. One explanation in line with the buzz literature (Hewett et al. 2016) is that elevated buzz levels due to a high number of new hires in the last or current year create a fertile ground for disproportionately more buzz and demand when even more hires are added.

In terms of demand, hiring quality is a double-edged sword. There are significant dynamic interactions and nonlinearities in the effect of the quality of spotlight personnel hiring on demand. As for the dynamic interaction effect, we find that if lagged hiring quality is high, the effect of hiring quality on demand is significantly negative in the long-term (Fig. 7a). If it is low, the effect is significantly positive in the long-term (Fig. 7b). Thus, high quality hires help lift demand, but only when there was an underinvestment in quality last year.

We also find a dynamic nonlinearity. Whereas the arc elasticity of a single-sized shock depicted in Fig. 7d is insignificant in the long term, the arc elasticity of a double-sized shock turns significant and negative in the long-term (Fig. 7e). The difference is significant in the long-term (Fig. 7f). Thus, the marginal demand effect of hiring quality becomes weaker as more quality is hired this year.

VAR-X showed a significant positive effect of hiring quality on demand, in line with the buzz argument. The findings from the LCP allow to build on this argument. The significant dynamic interactions and nonlinearities we find for the effect of hiring quality on demand uncover that it is a double-edged sword. If used sparingly, hiring quality drives demand but too much of it does not help. One explanation in line with the buzz argument is that customers get excited about hiring quality as long as it remains special. Once it becomes the new normal, anticipation and thus incremental demand wears off.

INVESTMENT SCENARIOS

To gauge real-world effect sizes and to illustrate the consequences of hiring decisions in professional soccer, we compare several scenarios that speak to the tradeoffs and interactions between hiring quantity and hiring quality. We use 2019 numbers of the three major leagues as the baseline, including the average number of new players hired (13.9 but rounded to 14 in the text below) and the average spend per player (€1.44M in 2019 Euros).

We begin with assuming a windfall that can be invested in hiring players. In scenario one, a team hires one standard deviation (rounded to 5) more new players than average, each at the average price (€1.44M). This equates to an additional spend of 5×€1.44M = €7.18M in total.

In scenario two, the same windfall is used to hire an average number of new players (14) yet at a higher average price of €1.95M (=€1.44M+€7.18M/14). To evaluate each scenario, we use GIRF-sized shocks reflecting the correlations between the shocked endogenous variable (hiring quantity vs hiring quality) and the other endogenous variables.

For both scenarios, we use the LCP results to predict change in winning percentage (service performance) and ticket sales (demand) translated into monetary terms (average ticket price: €50; average stadium size: 42,000; home games played per season: 17; Gottschalk 2019). Table 4 contains cumulative effect sizes. Table 4 shows that hiring five more players than average *decreases* winning percentage by 3.81 percentage points while it *increases* ticket sales by €2.06M. Conversely, using the windfall to raise average quality leads to a total *increase* in ticket sales of €46.7K but also *increases* the total winning percentage by .61 percentage points. Putting the numbers into perspective, we note that most recently the average revenue per team in the relevant leagues was €130M and that even one more win can be enough to go up one or more ranks in their league (DFL 2020). One rank is decisive if it qualifies a team for the Champions League tournament or triggers relegation into a lower league. Both events have major financial implications. Thus, the results indicate that the real-world impact of hiring players is substantial.

--- Insert Table 4 about here ---

While the previous scenarios assume that there is a windfall, in which case teams have more money to spend, budgets are often fixed: an increase in hiring quantity implies a decrease in hiring quality and vice versa. The next set of scenarios reflects this by fixing the hiring budget at the average amount spent by teams in the major leagues on hiring players in the most recent observation period (all in 2019 Euros): €20.16M, calculated as the product of the average hiring quantity (14 new players) and average hiring quality (average spend of €1.44M per new player).

With the hiring budget held constant across scenarios, we compare two hiring strategies that trade off hiring quantity (number of new players) against hiring quality (average transfer spend per player): a *concentrated investment*, where a team hires fewer new players than average at an above average quality (14-5=9 new players; average spend of €2.24M); and a *spread-out investment*, where a team hires more players than average at a below average quality (14+5=19 new players; average spend of €1.06M). Again, we use GIRF-sized shocks reflecting the correlations between the *two* shocked endogenous variables in each strategy (high quality & low quantity vs low quality & high quantity), respectively, and the other endogenous variables.

We overlay both strategies with three hypothetical legacies to assess how outcomes depend on the hiring variables' history: a *balanced legacy* with lagged hiring quantity and quality at their means; a *concentrated legacy* with lagged hiring quantity below average (9=14-5) and lagged hiring quality above average (€2.24M); and a *spread-out legacy* with lagged hiring quantity above average (14+5=19) and lagged hiring quality below average (€1.06M).

For each of the two hiring strategies and three legacies, we use LCPs to predict change in winning percentage and monetary ticket sales using the same assumptions as before (Figure 8). Throughout the three different legacies, a concentrated investment has a positive effect on the cumulative winning percentage across seasons (up to more than 7 percentage points) yet a negative effect on ticket sales (up to −€1.59M), while a spread-out investment has a negative effect on performance (up to approximately −5 percentage points) yet a positive effect on ticket sales (up to +€2.0M). The effect sizes are substantial, especially given that they were achieved by the same hiring budget, spent differently.

The effects differ across the legacies. A concentrated investment is most effective for winning if there is a spread-out legacy (Fig. 8a) and a spread-out investment is least detrimental if combined with a spread-out legacy (Fig. 8b). A concentrated investment is most detrimental for ticket sales with a spread-out legacy (Fig. 8c). For ticket sales, the most beneficial combination is a spread-out investment with a spread-out legacy (Fig. 8d).

All in all, Figure 8 shows that different investment strategies prevail, depending on the legacy and the focal performance metric (winning or ticket sales). If the primary goal is winning, concentrated investments triumph, especially when there is a spread-out legacy (but this goes at the expense of ticket demand). If the primary goal is ticket demand, spread-out investments win, especially when there is a spread-out legacy (but this comes at the expense of winning).

--- Insert Figure 8 about here ---

DISCUSSION

Providers of ongoing entertainment experiences have to hire new spotlight personnel and let go of existing ones. This poses a dilemma: changes in spotlight personnel may harm service performance but they may also benefit demand or vice versa. To address this dilemma we offer the first-ever systematic examination of the impact of the quantity and quality of spotlight personnel hiring and turnover on both outcomes, taking into account the dynamic nature of the effects and the possibility of interactions and nonlinearities.

Theoretical Implications

This paper offers several contributions. We address the recent calls for marketing research to examine the role of human capital for service marketing outcomes (Kalaignanam et al. 2021; Moorman and Day 2016). We respond to these calls by defining spotlight personnel, by distinguishing them from other personnel and by investigating their role for service performance and demand. The focus on spotlight personnel sets the study apart from papers that have focused on other personnel mentioned in Figure 1 such as frontline staff (Bendapudi and Leone 2002; Shi et al. 2017) and top management (Germann, Ebbes, and Grewal 2015; You et al. 2020).

Implications for sales and service research. This literature has just begun to explore the role of personnel for firm performance (Hogreve et al. 2017). While the few existing papers focus on the consequences of turnover (Tremblay 2020; Shi et al. 2017), we contribute by examining the consequences of hiring *and* turnover. The new insight is that *hiring* decisions are more consequential than *turnover*, at least for spotlight personnel.

Implications for management research. Management research has largely focused on *frontline staff*, assuming that the effects of changes to personnel have the *same* direction for proximal outcomes (e.g., service performance) and distal outcomes (e.g., demand). A key insight we contribute to this literature stream is that changes in *spotlight personnel* can lead to *opposing* outcomes for proximal and distal outcomes. We show that the key to avoid this dilemma is a focus on hiring quality (rather than quantity) because it has beneficial effects on both outcomes. The key implication for management research is that it should be tested to which degree findings that are primarily based on frontline staff indeed generalize to other personnel, including spotlight personnel but also enabling staff and key decision makers (see Figure 1).

Implications for entertainment/movie research. Entertainment research in marketing has focused on the *short-term* (concurrent) effect of *hiring* stars in movies (e.g., Carrillat, Legoux, and Hadida 2018, Hofmann et al. 2017), in sports teams (Yang, Shi, and Goldfarb 2009) and in Broadway shows (Han and Ravid 2020). While we also offer a more comprehensive consideration of spotlight personnel than stars only, the key insights that we contribute to this stream are that (i) a large portion of the hiring effect plays out in the *long term* and (ii) that spotlight personnel *turnover* has also performance implications (selling quality spotlight personnel leads to a drop in demand). We encourage entertainment researchers to account for dynamic effects of spotlight personnel changes and for turnover of spotlight personnel.

Practical Implications

The study has important implications for entertainment providers that rely on spotlight personnel for ongoing service provision.

Hires are more consequential drivers of service performance and demand than turnover. Our results suggest that providers should generally focus their attention on spotlight personnel hiring as it is more consequential than turnover. Only turnover quality had a significant negative effect on demand so it is recommendable to avoid high quality turnover of spotlight personnel. On the hiring side the implications are much richer so we focus on them next.

Hiring quantity has conflicting implications for service performance and demand. Provider concerns about a dilemma associated with hiring spotlight personnel (increasing demand paired with decreasing service performance) are justified. We show that the dilemma arises from hiring quantity. Providers that prioritize demand over service performance can choose to push demand by hiring many new spotlight personnel. Providers that prioritize service performance over demand should only make as many changes in spotlight personnel as necessary. For providers who adopt a more balanced approach to achieving both goals, we recommend selecting high quality hires as we discuss next.

Hiring quality is great, but it should be used sparingly. Investing in the quality of new hires is rewarded as it contributes significantly to increasing service performance as well as demand. There is one constraint, though. When the average quality hired is very high (relative to the provider's usual quality hired), these desirable consequences wear off. Hence, and because top quality spotlight personnel are very expensive, we recommend hiring them sparingly.

The effects of changes in spotlight personnel fully play out in the long run. Consistent with the notion that spotlight personnel are critical for service performance and demand, another important implication of this study is that hiring decisions can echo for years both in terms of service performance and demand. Providers should keep this in mind when they define their spotlight personnel hiring strategy and performance metrics.

Methodological Implications

We are the first to borrow local (cubic) projections (Jordà 2005) from the economics literature and to apply them to a marketing problem. The LCP approach adds value beyond VAR models because it allows for flexible data exploration, unlike VAR-X models. While VAR-X models can be extended with interactions, nonlinearities and asymmetries, it is often very hard to theoretically argue for their inclusion or exclusion (Lehmann 2020). Often, thus, only few of them are explicitly modeled, which may lead to incorrect inferences. LCPs offer an elegant solution to that problem by inherently modeling these relationships flexibly. We propose that LCPs deserve a prominent role in in the toolbox of marketing researchers as complimentary tool to VAR models, in line with the use of local projections in economics and finance. Any area in which marketing researchers have used VAR models may benefit from using LCPs for more flexible exploration, particularly when nonlinear or interactive effects play a role (e.g., for word-of-mouth in social media or buzz across different media; Hewett et al. 2016; Trusov, Bucklin, and Pauwels 2009) but also when effects could be asymmetric (e.g., for service quality disruptions; Gijsenberg, van Heerde, and Verhoef 2015).

Limitations and Suggestions for Future Research

The limitations of this paper open avenues for future research. One is to test generalizability of the findings in other contexts. Next, we focus on players because they are clearly spotlight personnel, delivering the core service and being in the public spotlight.

However, other personnel (e.g., coaches) may also be involved in service delivery and attract public attention. Future research could capture the extent to which an employee is spotlight personnel through a continuous index. In addition, European soccer has gone through changes during the observation period (e.g., changes in TV rights, increased global appeal of soccer, competition between European leagues). While we use a rich sample (89% of all tickets sold in the observation period), studying other demand metrics would be useful. Likewise, transfer fees are subjective, negotiated measures of quality so it would be useful to study alternative measures for player quality, such as goals, assists, successful passes or recoveries. In addition, it would be interesting to separate the hiring of spotlight personnel from national competitors (i.e., directly adversely affecting a competitor's performance) from hiring top spotlight personnel from abroad (where the whole competitive system may benefit). Moreover, future research could study the role of organically grown spotlight talent as opposed to hired talent. In sports, youth development systems from teams such as Ajax Amsterdam are world-leading (Poli et al. 2021). Further, future research could develop a regime switching panel VAR model for testing how hosting major international events such as World Cups changes the dynamics studied in this paper. Finally, we account for commercial failure (relegation) and success (promotion) by including league fixed effects (five separate league dummies). However, future research can zoom in on how marketing approaches should adapt to commercial failure and success.

We hope that this research will be an impetus for additional research in marketing on the all-important marketing consequences of the "P" of personnel. After all, personnel is a key factor in service delivery and one of the greatest expenses for organizations. Data on the quality and quantity of personnel changes are increasingly accessible as are data of various performance metrics—example industries include TV shows, education and Broadway productions.

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Table 1. Research Informative about the Role of Changes in Spotlight Personnel for Provider Performance.

Study	Study Characteristics	Relevant Substantive Findings	Spotlight Personnel Hiring		Spotlight Personnel Turnover		Effect on Service Performance		Effect on Demand	
			Quan-tity	Qual-ity	Quan-tity	Qual-ity	Short Term	Long Term	Short Term	Long Term
Yang, Shi, and Goldfarb (2009)	Team sports (NBA); cross-sectional; 199 observations	• Alliances between high brand equity sports players and medium brand equity sports teams add the most value.	✓	✓					✓	
Han and Ravid (2020)	Theatre (Broadway); cross-sectional; 332 observations	• Addition of a theater star increases ticket sales and ticket prices. • Departure of a theater star has no significant effect on ticket sales and ticket prices.		✓		✓			✓	
This Study	Team sports (Bundesliga); cross-sectional and longitudinal (panel); 1,310 observations	• Spotlight personnel hiring is more important for service performance and demand than spotlight personnel turnover. • Hiring quantity entails a dilemma as it decreases service performance but increases demand. • Hiring quantity is good for demand but even better if it is higher (dynamic interaction, dynamic nonlinearity). • Hiring quality increases both service performance and demand. • Hiring quality has a more positive dynamic effect on service performance and demand if it is used sparingly (dynamic interaction, dynamic nonlinearity). • Many effects fully play out in the long-term.	✓	✓	✓	✓	✓	✓	✓	✓

Note: "Short term" refers to a concurrent effect within the same time period, while "long term" refers to a dynamic effect in a later time period.

Table 2. Measures and Sources

Variable	Operationalization	Data Source	Literature Support
Endogenous variables			
ln Demand	Log percentage of stadium capacity utilization for national league matches in the respective year (i.e., average annual ticket sales relative to stadium capacity)	www.dfb.de	Bloom (1999); Lewis (2008)
ln Service Performance	Log percentage of wins out of all league games played in the respective year	www.dfb.de	Ertug and Castellucci (2013); Meire et al. (2019); Yang et al. (2009)
ln Hiring Quantity	Log number of new players in the respective year	www.transfermarkt.com	Robert, Marques, and Le Roy (2009)
ln Hiring Quality	Log euro amount a team spent on average for a new player in the respective year (i.e., sum of transfer fees divided by number of new players)	www.transfermarkt.com	Liu et al. (2016)
ln Turnover Quantity	Log number of sold players in the respective year	www.transfermarkt.com	Robert, Marques, and Le Roy (2009)
ln Turnover Quality	Log euro amount a team earns on average for a sold player in the respective year (i.e., sum of transfer fees divided by number of sold players)	www.transfermarkt.com	Liu et al. (2016)
Exogenous variables			
ln Team Age	Log years elapsed since market entry	www.dfb.de	Brown and Lattin (1994)
Three-league System	Dummy variable coded 1, if the German professional soccer consisted of a league system of three leagues, 0 else. The third league was introduced in the 2008-09 season	www.dfb.de	Own measure
League 1-League 5	Dummy variables coded 1, if the team played in the respective (professional) league, 0 else	www.dfb.de	Rickmann and Witt (2008)
Three Points	Step dummy variable for introduction of three-point system and the Bosman ruling in the 1995-96 season, coded 1 after, 0 before	www.dfb.de	Frick and Simmons (2008)
German Reunification	Step dummy variable for the integration of East Germany's top soccer clubs after German Reunification in the 1991-92 season, coded 1 after, 0 before	www.dfb.de	Own measure
Euro Introduction	Step dummy variable for the onset of the effect of the 2002 euro introduction, coded 1 after, 0 before	www.ecb.europa.eu	Brachinger (2006)
National Team Wins	Dummy variables coded 1, if the German national team won a title before the respective season, 0 else	www.dfb.de	Meier et al. (2016)
Ln Population Size	Log population size of the hometown in the respective season	Web search	Price and Sen (2003)

Table 3. Descriptive Statistics

Variable	Scale	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
				Correlations[a]																	
1. Demand	% of stadium capacity utilization (0-100%)	51.95	30.11	1.00																	
2. Service Performance	% wins (0-100%)	40.22	14.14	-.09	1.00																
3. Hiring Quantity	Number of new players	10.28	4.85	.18	-.11	1.00															
4. Hiring Quality	Euro amount a team spent on average for a new player	531k	1,439k	.67	-.04	.18	1.00														
5. Turnover Quantity	Number of sold players	10.37	5.20	.19	.00	.71	.22	1.00													
6. Turnover Quality	Euro amount a team earns on average for a sold player	374k	1,041k	.49	-.03	.22	.59	.32	1.00												
7. Team Age	Years elapsed since market entry	31.74	12.82	.41	-.03	.50	.43	.51	.39	1.00											
8. Three-league System	Step dummy (0-1)	.28	.45	.28	-.01	.38	.20	.39	.22	.57	1.00										
9. League 1	Dummy (0-1)	.52	.50	.59	-.18	-.16	.54	-.12	.36	.12	-.05	1.00									
10. League 2	Dummy (0-1)	.29	.46	-.14	-.02	.15	-.15	.09	-.08	-.09	-.01	-.67	1.00								
11. League 3	Dummy (0-1)	.14	.35	-.47	.19	-.06	-.43	-.04	-.32	-.11	-.01	-.43	-.26	1.00							
12. League 4	Dummy (0-1)	.03	.18	-.28	.12	.12	-.24	.12	-.16	.07	.12	-.20	-.12	-.08	1.00						
13. League 5	Dummy (0-1)	.00	.07	-.14	.10	.08	-.09	.08	-.07	.05	.11	-.07	-.04	-.03	-.01	1.00					
14. Three Points	Step dummy (0-1)	.60	.49	.37	-.02	.54	.32	.52	.35	.71	.50	-.04	-.01	.01	.11	.05	1.00				
15. German Reunification	Step dummy (0-1)	.71	.46	.33	-.01	.51	.36	.50	.36	.69	.40	-.06	.01	.02	.07	.04	.80	1.00			
16. Euro Introduction	Step dummy (0-1)	.48	.50	.36	-.01	.48	.27	.50	.29	.69	.65	-.05	-.01	-.01	.14	.07	.77	.62	1.00		
17. National Team Wins	Step dummy (0-1)	.13	.33	.02	.02	.00	.00	.01	.01	-.01	.11	.00	-.01	.00	.04	-.03	.00	-.08	-.06	1.00	
18. Population size	Population size of hometown	603k	665k	.11	.03	.01	.21	.01	.18	.15	.02	.17	-.05	-.13	-.08	-.04	.02	.03	.02	.01	1.00

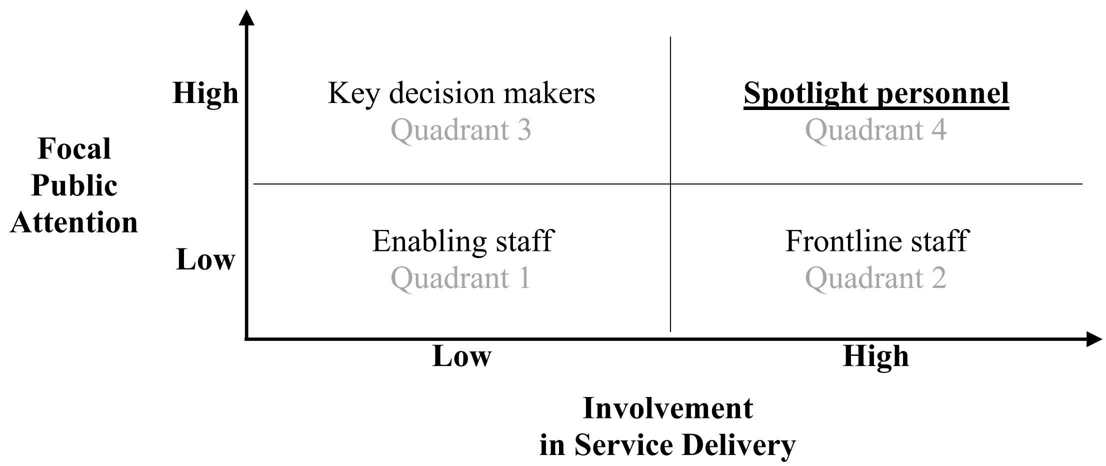
Notes: Correlations greater than or equal to .05 are significant ($p < .05$, two-tailed). [a] Correlations are based on logs for variables 1-7 and 18, consistent with the model specification.

Table 4. Real-world Effect Sizes of Hiring New Players

		Cumulative Change in Winning Percentage		Cumulative Change in Ticket Revenue	
Windfall to spend	**One-off Change in Hiring**	**Elasticity**	**Change in Winning Percentage Points**	**Elasticity**	**Monetary Change**
€7,176,000	Five additional players hired at average price (€1,435,000)	-.263	-3.81	.217	€2,059,249
€7,176,000	Average number of players hired at higher average price (€1,951,400)	.042	.61	.005	€46,739

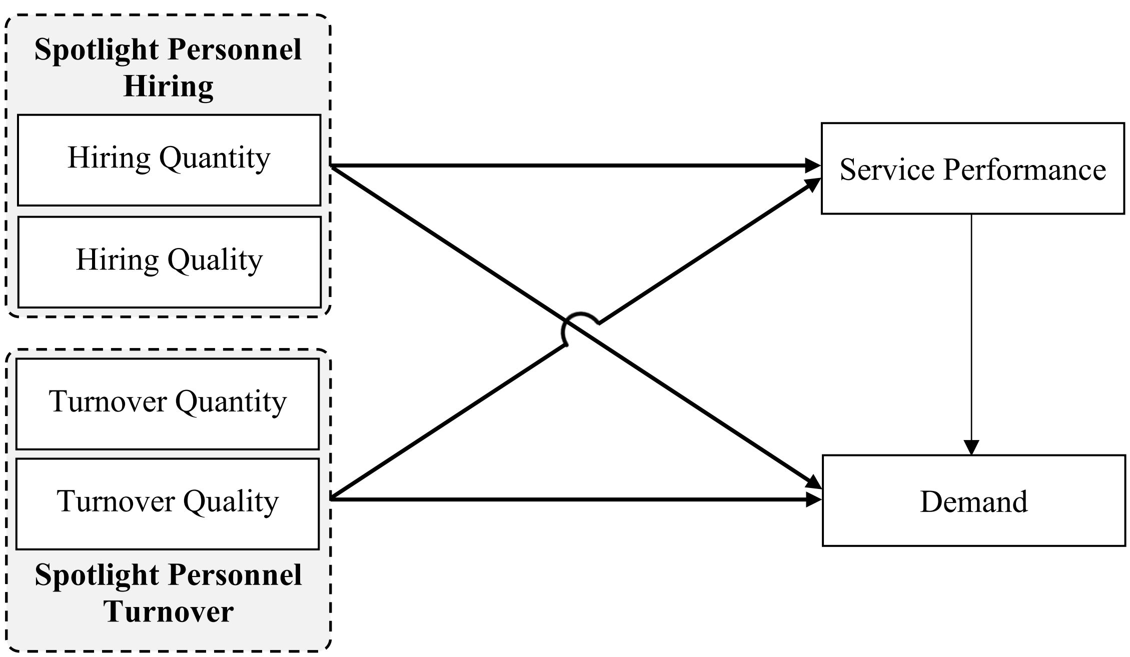
Notes: Results are based on contemporaneous effects and LCP using forecasting horizons for which the GIRF is significant ($p < .05$). Elasticities are based on arc elasticities. Assumptions: average ticket sales price = €50, average stadium capacity = 42,000, 17 home games per season. Monetary values in 2019 Euros.

Figure 1: Spotlight Personnel Attract Focal Public Attention while They Deliver the Service



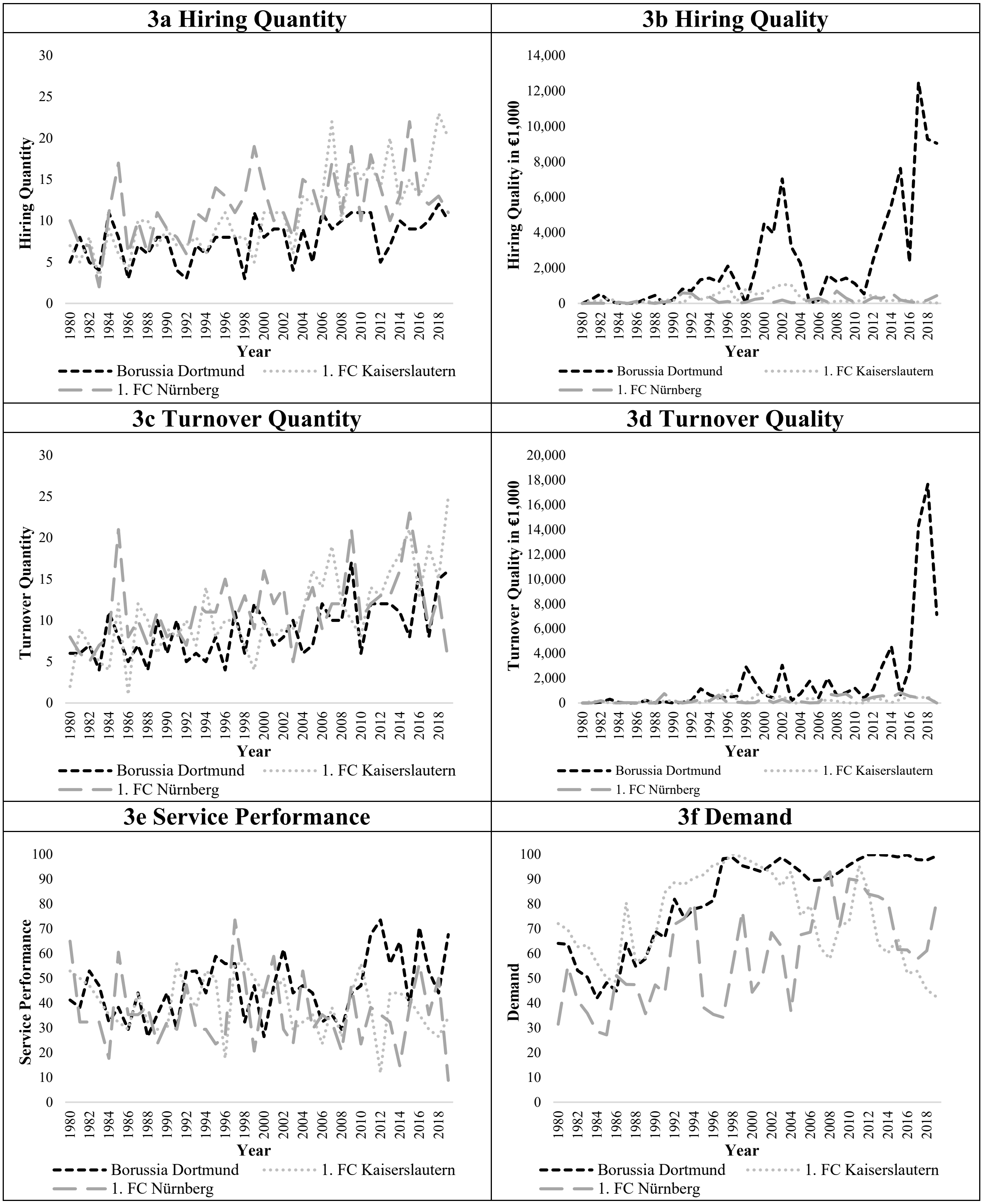
Note: Spotlight personnel are emphasized because they are the focus in this research.

Figure 2: Study Framework



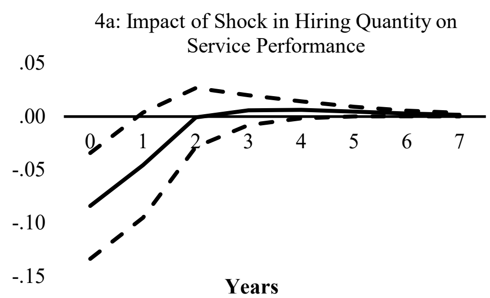
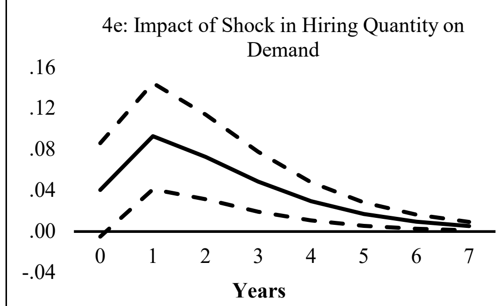
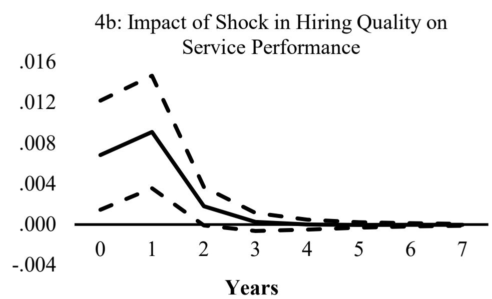
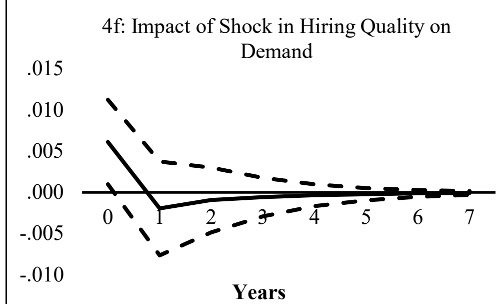
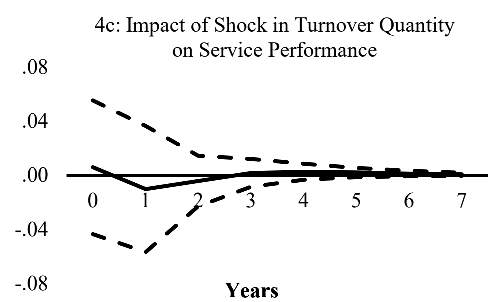
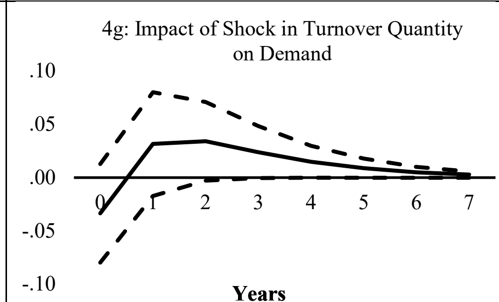
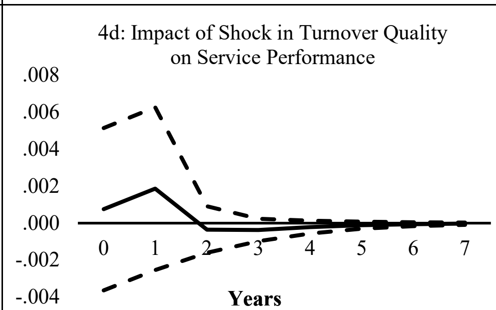
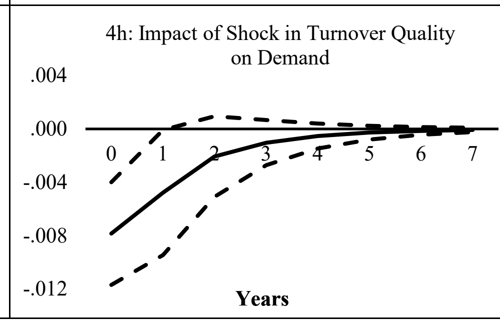
Notes: Focal effects are bold arrows. All depicted variables are endogenous variables in the empirical study. Not depicted in the figure, the empirical study also accounts for dynamic main effects between all endogenous variables, as well as dynamic interaction effects, dynamic nonlinear effects, and dynamic asymmetric effects.

Figure 3: Time Series of Focal Variables for Prototypical Teams



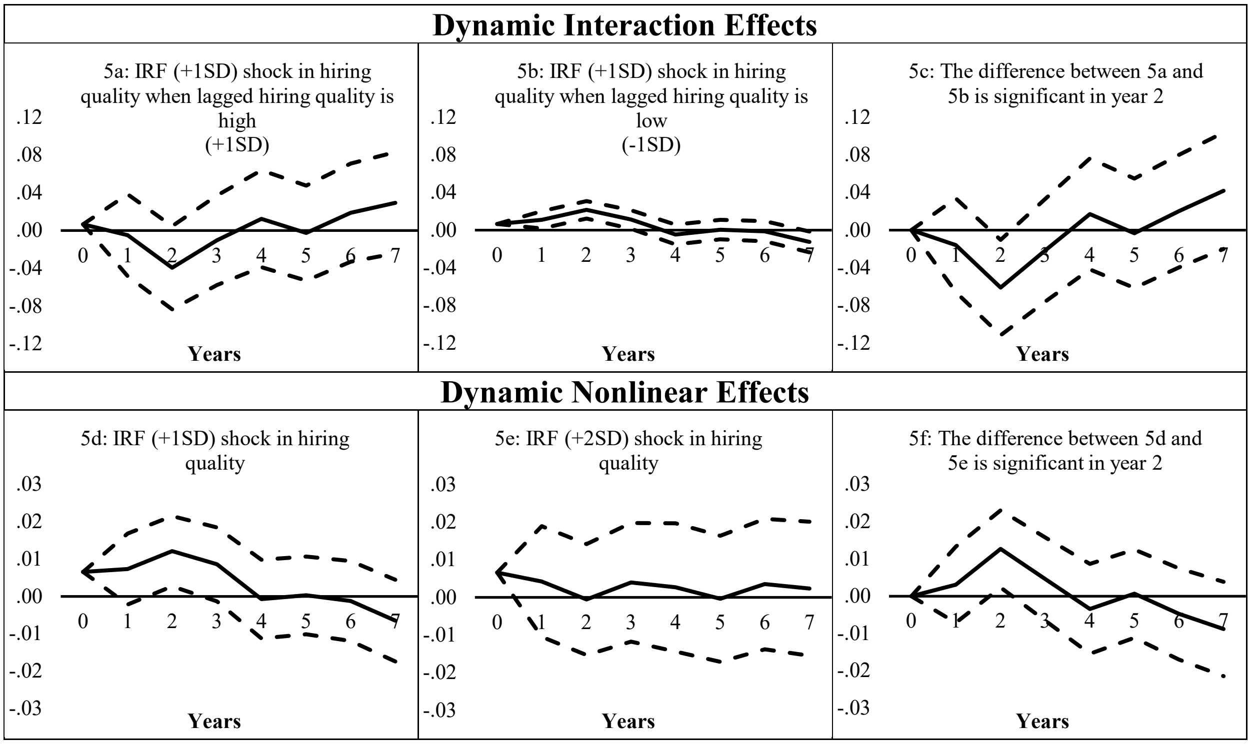
Notes: Reasoning behind prototypical team choice: Borussia Dortmund is the most successful team in terms of ticket demand. 1. FC Kaiserslautern has a long history but deteriorates continuously. 1. FC Nuremberg is a long-established team but has recently seen some ups and downs.

Figure 4: IRFs Showing the Focal Dynamic Effects based on VAR-X

Effect on… / Shock in…	ln Service Performance	ln Demand
ln Hiring Quantity		
ln Hiring Quality		
ln Turnover Quantity		
ln Turnover Quality		

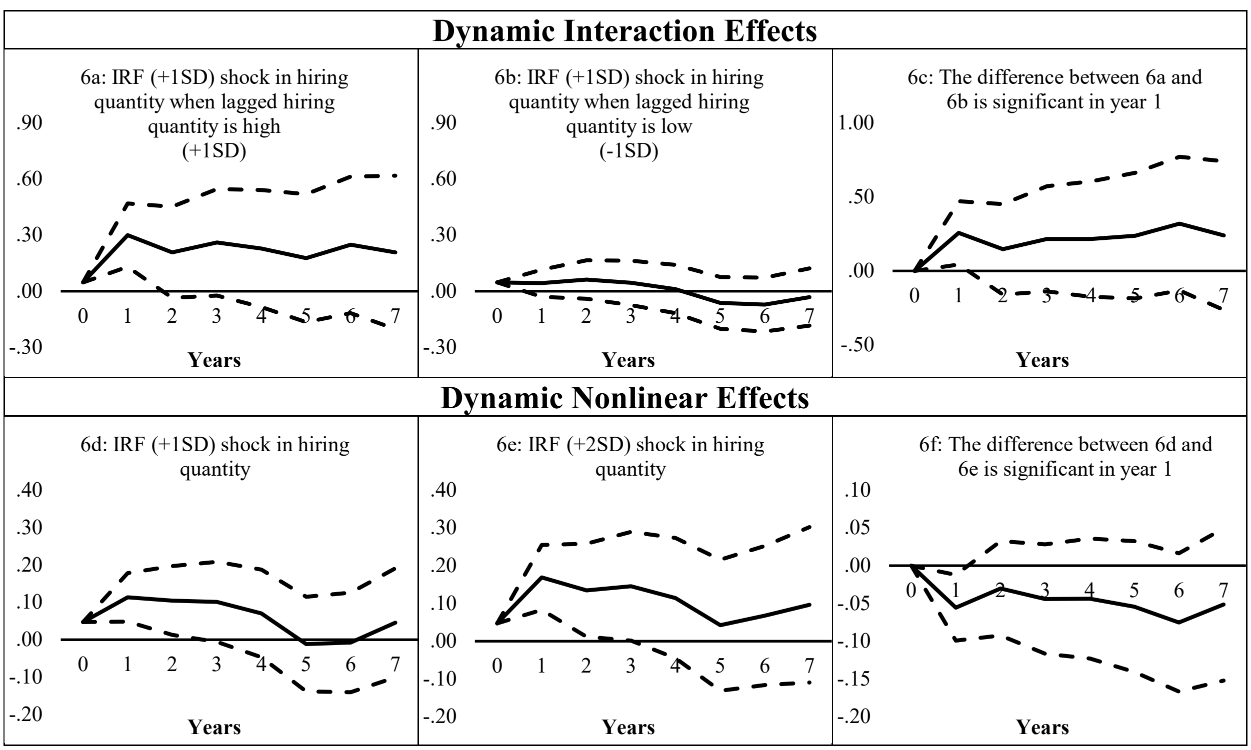
Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

Figure 5: LCP IRFs Showing the Flexible Dynamic Effects of Hiring Quality on Service Performance



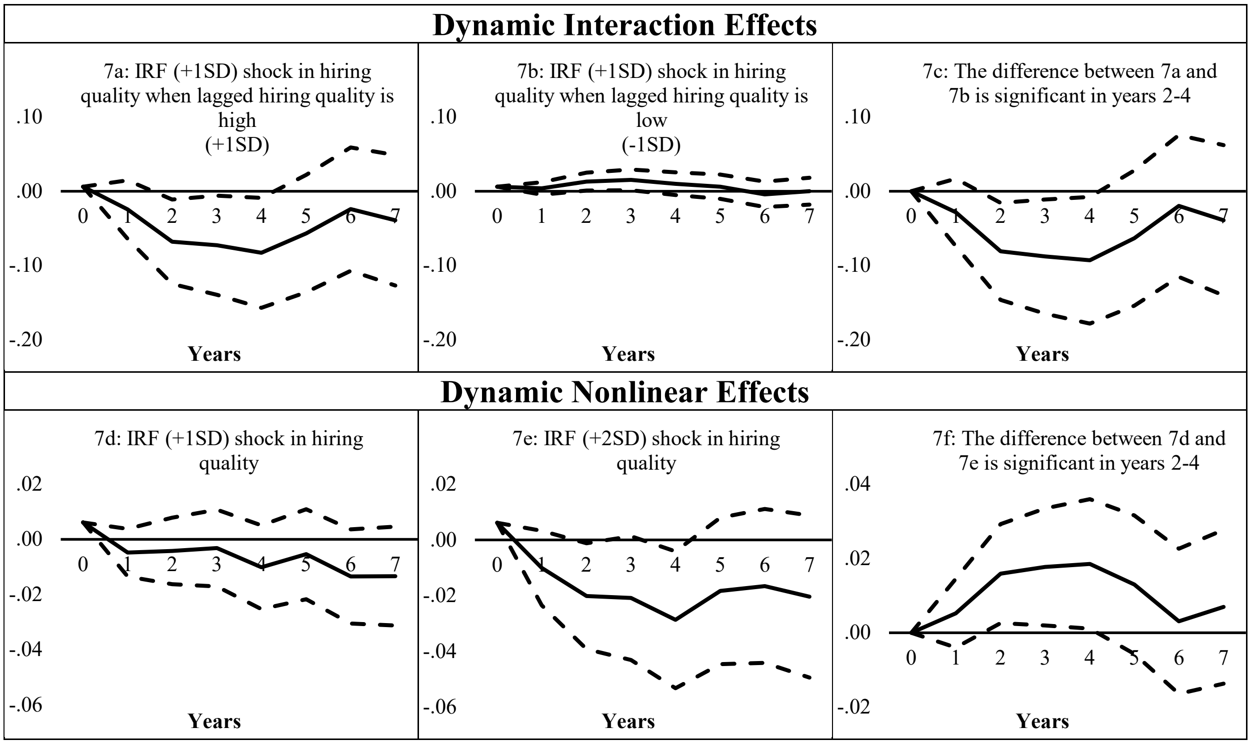
Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

Figure 6: LCP IRFs Showing the Flexible Dynamic Effects of Hiring Quantity on Demand



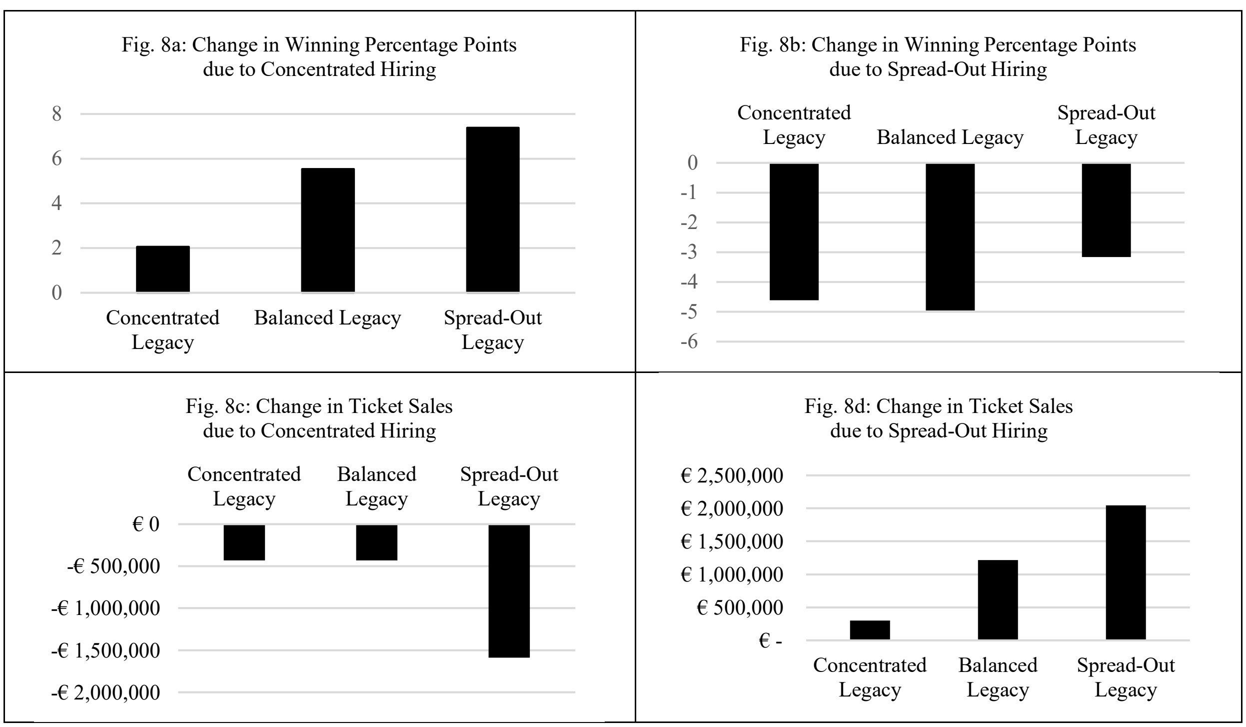
Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

Figure 7: LCP IRFs Showing the Flexible Dynamic Effects of Hiring Quality on Demand



Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

Figure 8: Cumulative Effects of Different Hiring Strategies for Different Legacies



Notes: Results are based on LCP using forecasting horizons for which IRF is significant ($p < .05$). Assumptions: average ticket sales price = €50, average stadium capacity = 42,000, 17 home games per season. Monetary values in 2019 Euros.

Web Appendix

Spotlight Personnel:
How Hiring and Turnover Drive Service Performance versus Demand

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OVERVIEW

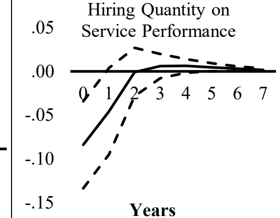
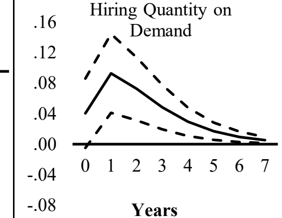
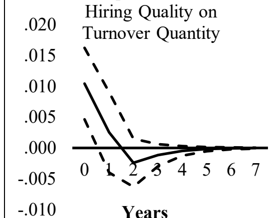
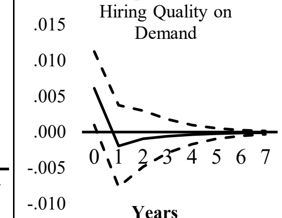
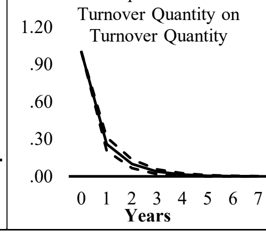
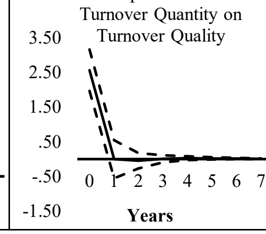
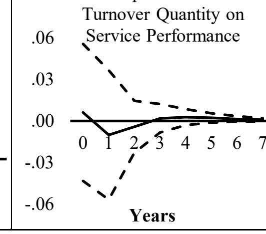
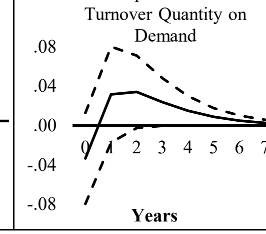
WEB APPENDIX A: PARAMETER ESTIMATES BASED ON VAR-X

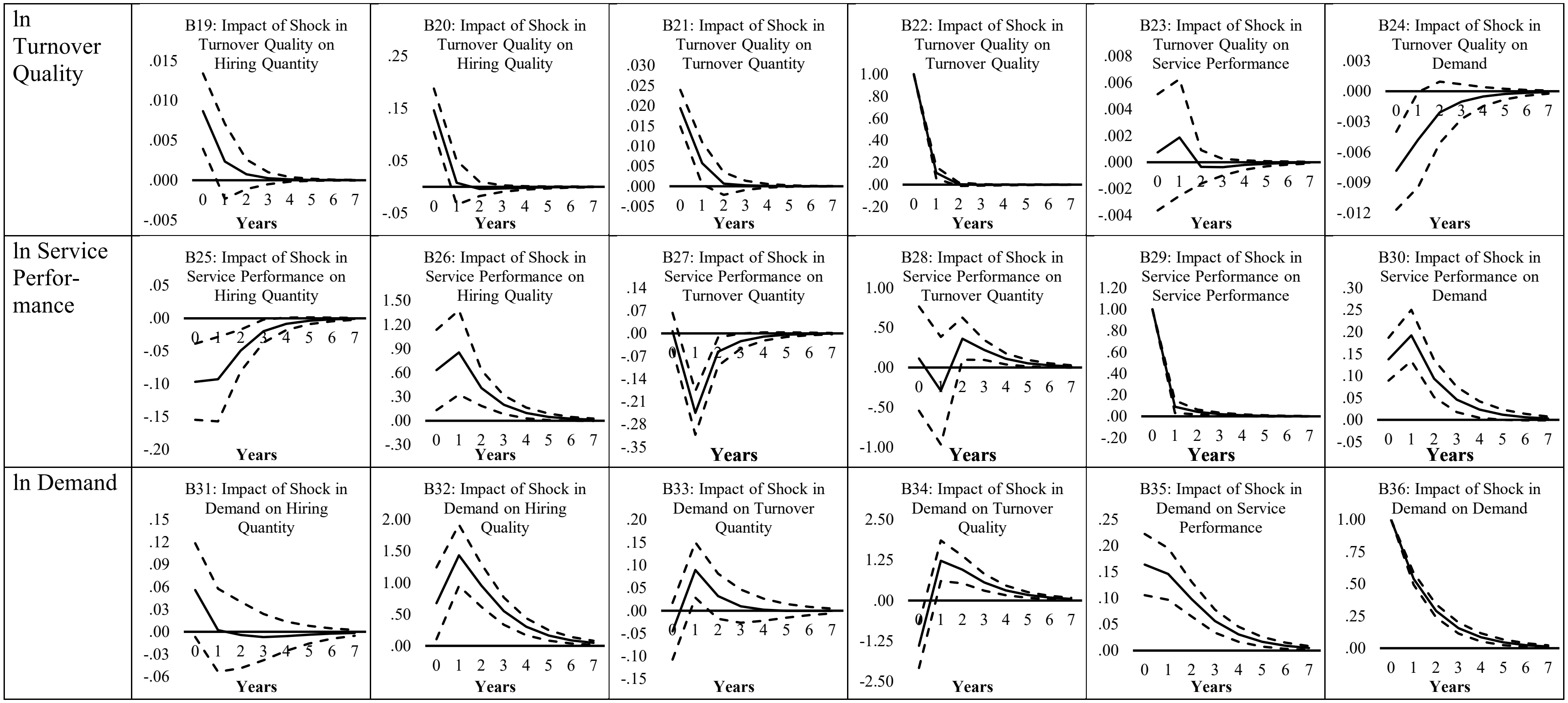
	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Demand	**.519**	**.138**	.006	**1.251**	**.107**	**1.405**
Lag ln Service Performance	**.133**	**.060**	-.071	**.586**	-.216	-.598
Lag ln Hiring Quantity	**.081**	-.059	**.223**	-.088	**.443**	-.281
Lag ln Hiring Quality	-.007	**.008**	-.003	**.136**	-.002	**.120**
Lag ln Turnover Quantity	.019	.009	**.083**	.031	**.056**	-.202
Lag ln Turnover Quality	-.001	.002	-.001	-.002	.002	**.107**
Ln Team Age	-.002	-.038	**.403**	**1.144**	**.280**	.952
Three-league System	**.088**	-.065	.013	.269	-.022	.251
League 1	**1.215**	-1.193	-.130	**7.911**	-.385	4.310
League 2	**.840**	-.847	-.063	**6.233**	-.293	4.106
League3	**.457**	-.501	-.215	3.597	-.234	2.782
League 4	.274	-.285	-.200	2.454	-.212	2.325
League 5	.014	.140	-.163	.381	-.123	1.056
Three Points	**.094**	-.040	**.106**	.082	-.029	.985
Euro Introduction	**.103**	-.023	-.038	-.221	.035	-.420
German Reunification	**.146**	-.044	.040	**2.353**	.051	**1.453**
National Team Wins	**.054**	.014	.016	.300	.019	.088
ln Population	.219	-.298	-.729	.660	-.644	1.546
1.FC Kaiserslautern	-2.432	**7.595**	**8.927**	-19.543	**8.252**	-23.975
1. FC Cologne	-3.065	**8.317**	**10.523**	-20.341	**9.767**	-25.686
1. FC Nuremberg	-2.876	**7.993**	**10.134**	-20.859	**9.316**	-25.482
1. FC Saarbruecken	-2.860	**7.676**	**9.446**	-22.634	**8.741**	-25.181
TSV 1860 Munich	-3.178	**8.269**	**10.782**	-21.055	**9.915**	-26.630
Arminia Bielefeld	-2.670	**7.773**	**9.895**	-21.947	**9.053**	-25.961
Bayer 04 Leverkusen	-2.579	**7.890**	**9.355**	-18.576	**8.796**	-23.000
FC Bayern Munich	-3.116	**8.879**	**10.577**	-19.621	**9.978**	-25.281
Borussia Dortmund	-2.868	**8.363**	**10.045**	-20.465	**9.427**	-24.588
Borussia Monchengladbach	-2.683	**7.921**	**9.495**	-20.346	**8.863**	-23.303
Eintracht Braunschweig	-2.623	**7.701**	**9.553**	-22.182	**8.788**	-27.062
Eintracht Frankfurt	-3.054	**8.191**	**10.339**	-21.159	**9.543**	-25.913
FC St. Pauli	-2.836	**8.206**	**11.014**	-22.507	**9.895**	-28.604
FSV Mainz 05	-3.131	**8.028**	**10.293**	-21.268	**9.510**	-26.566
Fortuna Dusseldorf	-2.776	**7.760**	**9.502**	-20.796	**8.813**	-23.821
Hamburger SV	-3.226	**8.572**	**11.005**	-20.110	**10.193**	-26.121
Hannover 96	-3.089	**8.087**	**10.171**	-21.642	**9.425**	-25.858
FC Hansa Rostock	-2.716	**7.523**	**9.314**	-22.387	**8.608**	-26.093
Hertha BSC Berlin	-3.545	**8.714**	**11.443**	-21.918	**10.599**	-27.834
KFC Uerdingen 05	-2.754	**7.823**	**9.642**	-21.704	**8.857**	-25.663
Karlsruher SC	-3.007	**7.641**	**9.827**	-18.821	**9.067**	-23.520

MSV Duisburg	-3.011	**7.968**	**10.106**	-22.216	**9.269**	-26.693
SC Freiburg	-2.589	**7.710**	**9.611**	-20.945	**8.866**	-24.105
SV Darmstadt 98	-2.774	**8.023**	**9.611**	-20.828	**8.973**	-24.481
SV Waldhof Mannheim	-2.570	**7.517**	**9.040**	-20.710	**8.465**	-22.906
FC Schalke 04	-3.244	**8.203**	**11.169**	-23.121	**10.192**	-27.369
SpVgg Greuther Fuerth	-2.732	**7.465**	**9.362**	-22.199	**8.604**	-25.060
SpVgg Unterhaching	-2.795	**7.763**	**9.992**	-22.380	**9.188**	-25.858
VfB Stuttgart	-3.013	**8.312**	**10.142**	-19.784	**9.472**	-24.605
VfL Bochum	-2.786	**7.894**	**9.972**	-21.956	**9.164**	-26.012
VfL Osnabrueck	-2.546	**7.549**	**9.477**	-21.733	**8.651**	-25.607
VfL Wolfsburg	-2.662	**7.681**	**8.958**	-19.040	**8.340**	-22.932
SV Werder Bremen	-2.884	**8.312**	**10.016**	-20.074	**9.343**	-25.401
Model fit: R^2	.508	.653	.581	.457	.291	.862

Notes: Significant parameters ($p < .05$) in bold.

WEB APPENDIX B: FULL SET OF IRF ELASTICITIES BASED ON VAR-X

Effect on… Shock in…	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality	ln Service Performance	ln Demand
ln Hiring Quantity	B1: Impact of Shock in Hiring Quantity on Hiring Quantity 	B2: Impact of Shock in Hiring Quantity on Hiring Quality 	B3: Impact of Shock in Hiring Quantity on Turnover Quantity 	B4: Impact of Shock in Hiring Quantity on Turnover Quality 	B5: Impact of Shock in Hiring Quantity on Service Performance 	B6: Impact of Shock in Hiring Quantity on Demand 
ln Hiring Quality	B7: Impact of Shock in Hiring Quality on Hiring Quantity 	B8: Impact of Shock in Hiring Quality on Hiring Quality 	B9: Impact of Shock in Hiring Quality on Turnover Quantity 	B10: Impact of Shock in Hiring Quality on Turnover Quality 	B11: Impact of Shock in Hiring Quality on Service Performance 	B12: Impact of Shock in Hiring Quality on Demand 
ln Turnover Quantity	B13: Impact of Shock in Turnover Quantity on Hiring Quantity 	B14: Impact of Shock in Turnover Quantity on Hiring Quality 	B15: Impact of Shock in Turnover Quantity on Turnover Quantity 	B16: Impact of Shock in Turnover Quantity on Turnover Quality 	B17: Impact of Shock in Turnover Quantity on Service Performance 	B18: Impact of Shock in Turnover Quantity on Demand 



Notes: — mean, --- 95% CI. The y-axes report arc elasticities.

WEB APPENDIX C: CORRELATIONS BETWEEN IRF EFFECTS OF ROBUSTNESS TESTS AND MAIN MODEL

Table C.1: Dynamic Effects Based on VAR-X

Investigated Effect		Alternative Time Spans						Omitting Teams		Variable Composition			
Shock in	Effect on	1975-2019	1978-2019	1982-2019	1985-2019	1980-2017	1980-2014	Two Best Teams Omitted	Two Worst Teams Omitted	Quality Measures = Max. spend, Max. earn	Demand Measure = Tickets Sold	Omit Observations with Full Stadium Utilization	Inclusion of Herfindahl Measures
Hiring Quantity	Service Performance	.963	.890	.988	.992	1.000	.986	.995	1.000	1.000	.963	1.000	.999
Hiring Quality	Service Performance	.994	.997	.994	.994	1.000	1.000	1.000	.998	1.000	.994	1.000	.999
Turnover Quantity	Service Performance	.986	.929	.902	.975	.985	.981	.964	.854	1.000	.986	.999	.913
Turnover Quality	Service Performance	.929	.973	.967	.657	.981	.944	.991	1.000	.995	.929	.996	.999
Service Performance	Service Performance	.999	.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	.999	1.000	1.000
Demand	Service Performance	.998	.992	.995	.997	1.000	.999	1.000	.999	1.000	.998	1.000	1.000
Hiring Quantity	Demand	.996	.996	.996	.973	.994	.999	1.000	.998	1.000	.996	1.000	.999
Hiring Quality	Demand	.992	.997	.949	.867	.998	.989	.999	.993	.987	.992	1.000	.997
Turnover Quantity	Demand	.949	.975	.992	.992	.995	.989	.997	.995	1.000	.949	1.000	.997
Turnover Quality	Demand	1.000	1.000	1.000	.999	1.000	.997	.999	.998	1.000	1.000	1.000	1.000

Table C.2: Dynamic Effects Based on LCP

Investigated Effect		Alternative Time Spans						Omitting Teams		Variable Composition			
Shock in	Effect on	1975-2019	1978-2019	1982-2019	1985-2019	1980-2017	1980-2014	Two Best Teams Omitted	Two Worst Teams Omitted	Quality Measures = Max. spend, Max. earn	Demand Measure = Tickets Sold	Omit Observations with Full Stadium Utilization	Inclusion of Herfindahl Measures
Hiring Quantity	Service Performance	.882	.942	.983	.984	.930	.957	.990	.986	.994	.998	.999	.894
Hiring Quality	Service Performance	.975	.983	.992	.944	.991	.970	.995	.987	.994	.996	.999	.996
Turnover Quantity	Service Performance	.801	.954	.953	.859	.904	.793	.974	.991	.996	.991	.998	.528
Turnover Quality	Service Performance	.963	.992	.976	.976	.990	.971	.993	.992	.999	.999	.999	.948
Service Performance	Service Performance	.998	1.000	1.000	.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Demand	Service Performance	.918	.920	.995	.921	.993	.971	1.000	.995	.996	.943	1.000	.991
Hiring Quantity	Demand	.981	.985	.994	.972	.993	.985	.997	.992	.995	.939	1.000	.878
Hiring Quality	Demand	.945	.973	.989	.947	.997	.985	.997	.993	.982	.906	1.000	.965
Turnover Quantity	Demand	.925	.929	.935	.574	.995	.954	.993	.984	.981	.970	.999	.735
Turnover Quality	Demand	.910	.988	.858	.690	.959	.963	.982	.987	.988	.951	1.000	.918

Table C.3: Flexible Dynamic Effects Based on LCP

Investigated Effect		Alternative Time Spans						Omitting Teams		Variable Composition			
Shock in	Effect on	1975-2019	1978-2019	1982-2019	1985-2019	1980-2017	1980-2014	Two Best Teams Omitted	Two Worst Teams Omitted	Quality Measures = Max. spend, Max. earn	Demand Measure = Tickets Sold	Omit Observations with Full Stadium Utilization	Inclusion of Herfindahl Measures
Dynamic Interaction Effects													
Hiring Quality	Service Performance	.944	.963	.998	.989	.985	.978	.996	.995	.976	.994	1.000	0.986
Hiring Quantity	Demand	.905	.959	.989	.950	.913	.838	.998	.920	1.000	.895	1.000	0.987
Hiring Quality	Demand	.990	.995	.991	.978	.987	.893	.996	.998	.990	.972	1.000	0.926
Dynamic Nonlinear Effects													
Hiring Quality	Service Performance	.952	.970	.998	.986	.987	.982	.994	.996	.977	.995	1.000	0.834
Hiring Quantity	Demand	.909	.960	.984	.966	.936	.881	.998	.913	1.000	.915	1.000	0.948
Hiring Quality	Demand	.989	.995	.991	.978	.986	.887	.994	.998	.992	.978	1.000	0.996

WEB APPENDIX D: MEDIATION ANALYSES

The study framework in Figure 2 suggests that service performance mediates the impact of hiring and turnover decisions on demand. While we are not aware of any possibilities to test for mediation effects in multi equation time series models with exogenous variables (see also Colicev et al. 2018; Zhao and Luo 2019), the following analyses provide some support for such a mediation mechanism.

We estimate two sets of mediation models with ln Demand as the dependent variable and ln Service Performance as the mediator to mimic our VAR-X model. Mediation Model A analyses the mediating effect of service performance in a setting where demand is a function of contemporaneous service performance, contemporaneous and lagged hiring and turnover variables, as well as the regular set of covariates as independent variables. This model mimics the short-run effects of the VAR model through contemporaneous effects and the dynamic effects through the lagged hiring and turnover variables:

Model A:

(W1) $\ln Demand_{it} = \boldsymbol{\beta}_{i0}^{A} + \boldsymbol{\beta}_{1}^{A} \ln ServicePerformance_{it} + \boldsymbol{\beta}_{2}^{A}\boldsymbol{z}_{it} + \boldsymbol{\beta}_{3}^{A}\boldsymbol{z}_{it-1} + \boldsymbol{\beta}_{4}^{A}\boldsymbol{x}_{it} + \boldsymbol{\varepsilon}_{1it}^{A},$

(W2) $\ln ServicePerformance_{it} = \boldsymbol{\gamma}_{i0}^{A} + \boldsymbol{\gamma}_{1}^{A}\boldsymbol{z}_{it} + \boldsymbol{\gamma}_{2}^{A}\boldsymbol{z}_{it-1} + \boldsymbol{\gamma}_{3}^{A}\boldsymbol{x}_{it} + \boldsymbol{\varepsilon}_{2it}^{A}$

where $\boldsymbol{z}_{it} = \begin{pmatrix} \ln HiringQuantity_{it} \\ \ln HiringQuality_{it} \\ \ln TurnoverQuantity_{it} \\ \ln TurnoverQuality_{it} \end{pmatrix}$, $\boldsymbol{\beta}_{i0}^{A}$ and $\boldsymbol{\gamma}_{i0}^{A}$ are team fixed effects, $\boldsymbol{\beta}_{1}^{A}$ is the impact of service performance (the mediator) on demand, $\boldsymbol{\beta}_{2}^{A}$, $\boldsymbol{\beta}_{3}^{A}$, $\boldsymbol{\gamma}_{1}^{A}$, and $\boldsymbol{\gamma}_{2}^{A}$ are 4×1 vectors of coefficients which represent the contemporaneous and lagged effects of the hiring and turnover variables on demand and service performance, respectively, $\boldsymbol{x}_{it}$ is the $K \times 1$ vector of K exogenous variables also used in equation (1) of the paper, $\boldsymbol{\beta}_{4}^{A}$ and $\boldsymbol{\gamma}_{3}^{A}$ are $1 \times K$ matrix of coefficients and $\boldsymbol{\varepsilon}_{1it}^{A}$ and $\boldsymbol{\varepsilon}_{2it}^{A}$ are error terms with mean zero.

As an alternative to Model A, we also specify Model B, which examines the mediating effect of performance in a setting where demand is a function of lagged demand, contemporaneous and lagged service performance, contemporaneous and lagged hiring and turnover variables, as well as the regular set of covariates as independent variables. Model B mimics the dynamics of a VAR model by including autoregressive endogenous variables for ln Demand and ln Service Performance as predictors in their models.

Model B:

$$\text{(W3)} \ln Demand_{it} = \boldsymbol{\beta_{i0}^B} + \boldsymbol{\beta_1^B} \ln ServicePerformance_{it} + \boldsymbol{\beta_2^B z_{it}} + \boldsymbol{\beta_3^B w_{it-1}} + \boldsymbol{\beta_4^B x_{it}} + \boldsymbol{\varepsilon_{1it}^B},$$

$$(W4) \ln ServicePerformance_{it} = \boldsymbol{\gamma_{i0}^B} + \boldsymbol{\gamma_1^B z_{it}} + \boldsymbol{\gamma_2^B w_{it-1}} + \boldsymbol{\gamma_3^B x_{it}} + \boldsymbol{\varepsilon_{2it}^B}$$

where $\boldsymbol{z_{it}} = \begin{pmatrix} \ln HiringQuantity_{it} \\ \ln HiringQuality_{it} \\ \ln TurnoverQuantity_{it} \\ \ln TurnoverQuality_{it} \end{pmatrix}$, $\boldsymbol{w_{it-1}} = \begin{pmatrix} \ln Demand_{it-1} \\ \ln ServicePerformance_{it-1} \end{pmatrix}$, $\boldsymbol{\beta_{i0}^B}$ and $\boldsymbol{\gamma_{i0}^B}$ are team fixed effects, $\boldsymbol{\beta_1^B}$ is the impact of service performance (the mediator) on demand**,** $\boldsymbol{\beta_2^B}$ and $\boldsymbol{\gamma_1^B}$ are 4×1 vectors of coefficients which represent the direct effects of the hiring and turnover variables, and $\boldsymbol{\beta_3^A}$ and $\boldsymbol{\gamma_2^B}$ are 2×1 vectors of coefficients which represent the direct effects of lagged demand and service performance on demand and service performance, respectively. As before, $\boldsymbol{x_{it}}$ is the $\text{K} \times 1$ vector of K independent variables also used in equation (1) of the paper, $\boldsymbol{\beta_4^B}$ and $\boldsymbol{\gamma_3^B}$ are $1 \times K$ matrix of coefficients and $\boldsymbol{\varepsilon_{1it}^B}$ and $\boldsymbol{\varepsilon_{2it}^B}$ are error terms with mean zero.

Both mediation models can be considered structural versions of the VAR-X model used in our paper. In Mediation Model A we can use the product of $\boldsymbol{\beta_1^A}$ and $\boldsymbol{\gamma_1^A}$ $\boldsymbol{(\gamma_2^A)}$ to calculate the indirect effect of the contemporaneous (lagged) hiring and turnover variables on demand. In Mediation Model B we use the product of $\boldsymbol{\beta_1^B}$ and $\boldsymbol{\gamma_1^B}$ to assess the indirect effects of the contemporaneous hiring and turnover variables.

Table *D*.1: Mediation Analyses of Structural Restrictions

	Mediation Model A		Mediation Model B	
	ln Demand	ln Service Performance	ln Demand	ln Service Performance
Lag ln Demand			**.504**	**.131**
ln Service Performance	**.225**		**.134**	
Lag ln Service Performance			**.122**	.051
ln Hiring Quantity	.057	**-.121**	**.089**	**-.117**
Lag ln Hiring Quantity	**.133**	-.048		
ln Hiring Quality	**.014**	**.010**	**.006**	**.008**
Lag ln Hiring Quality	.002	**.009**		
ln Turnover Quantity	.002	**.060**	-.015	.036
Lag ln Turnover Quantity	.002	.017		
ln Turnover Quality	-.004	.001	**-.010**	.001
Lag ln Turnover Quality	-.002	.001		
ln_brandmaturity	-.073	-.029	.017	-.026
Intro3	**.205**	-.036	**.093**	**-.061**
liga1	**2.431**	**-.999**	**1.289**	**-1.183**
liga2	**1.760**	**-.699**	**.896**	**-.836**
liga3	**1.061**	**-.417**	**.495**	**-.502**
liga4	**.630**	-.243	.301	-.287
liga5	.186	.175	.009	.132
ThreePoint	**.182**	-.006	**.100**	-.023
euro	**.241**	.006	**.109**	-.025
GERreunion	**.196**	-.045	**.132**	-.039
NationWins	**.070**	.018	**.051**	.015
ln_population	.350	-.380	.243	-.335
Club fixed effects	included	included	included	included
Indirect effects on ln Demand via ln Service Performance				
ln Hiring Quantity	**-.027**		**-.029**	
Lag ln Hiring Quantity	-.011			
ln Hiring Quality	**.002**		**.002**	
Lag ln Hiring Quality	**.002**			
ln Turnover Quantity	.014		.012	
Lag ln Turnover Quantity	.004			
ln Turnover Quality	.000		.000	
Lag ln Turnover Quality	.000			
Model fit: R^2	.814	.288	.867	.298

Notes: Significant parameters (p<.05) in bold. Significance of indirect effects based in 500 bootstraps. Club fixed effects included in estimation.

Table D.1 shows the results. In both mediation Models A and B we find evidence that objective service performance partially mediates the effect of hiring decisions on demand. Both mediation models show that contemporaneous hiring quantity has a negative indirect effect (-.027 and -.029, respectively) on demand via service performance whereas contemporaneous hiring quality has a positive indirect effects (.002 in both models) on demand via service performance. Lagged hiring quality has a positive contemporaneous effect (.002) on demand via service performance.

The findings suggest that while the demand effects of hiring decisions (quantity and quality) are partially mediated by service performance, turnover quality has a direct negative impact on demand (-.010 in Model B).

WEB APPENDIX E: AN INTRODUCTION TO LOCAL PROJECTIONS

Local Projections Model Description

Local Projections (LPs) are a relatively new method for time series analysis (Jordà 2005). They belong to the family of direct multiperiod forecasting approaches and operate fundamentally different from VAR models (see also Figure E.1). While both methods aim to estimate impulse response functions (IRFs), i.e., the evolution of a variable of interest along a specified time horizon after a shock at a given moment, they differ in how they obtain these impulse responses. VARs estimate one regression using all data and thus provide one global approximation of the data generation process. They then apply iterative multiperiod forecasting to obtain the IRFs. In contrast, LPs use a collection of sequential regressions, where the endogenous variables are shifted one step further into the future for each regression, so-called local projections. Each of the local projections directly matches model estimation (for each forecast horizon) and key purpose (obtaining an impulse response estimate for each horizon). Combining the collection of impulse estimates for different horizons comprises the LP IRF.

We use an example with *n* endogenous variables and no exogenous variables to introduce local projections. We briefly revisit the well-known VAR model before introducing local projections to facilitate comparison. Let $\boldsymbol{y_t}$ be a *n* x 1 vector of endogenous variables observed in time periods *t*= 1,…,*T*. A standard VAR models this vector as a function of its own *P* lags to approximate the data generating process:

(W5) $\boldsymbol{y_t = \alpha_{VAR} + \Phi_1\, y_{t-1} + \cdots + \Phi_P\, y_{t-P} + v_t}$,

where $\boldsymbol{\alpha_{VAR}}$ is a *n* x 1 vector of parameters, $\boldsymbol{\Phi_p}$, *p=1,…,P*, a *n* x *n* matrix of parameters and $\boldsymbol{v_t}$ a vector of normal distributed error terms with mean zero and covariance matrix $\boldsymbol{\Sigma}$ (e.g., Pesaran and Shin 1998). The VAR model in (W5) can be extended to a VAR-X model that includes additional exogenous variables.

In VAR models (and local projections) it is infeasible to interpret estimated coefficients directly (Sims 1980).[14] Instead the individual coefficients of $\boldsymbol{\Phi}_{\mathbf{p}}$ are used to calculate impulse response functions after the VAR has been estimated (e.g., Trusov, Bucklin, and Pauwels 2009). An impulse response function is the difference between two forecasts, one with a shock in the error term at time *t* ($\boldsymbol{v}_{it} = \boldsymbol{d}$) and one without such a shock ($\boldsymbol{v}_{it} = \mathbf{0}$). For the standard VAR, the IRF is calculated by assessing how the shock in the error term at time *t* propagates to time *t*+1, which then carries over to time *t*+2, etc. (Pesaran and Shin 1998):

(W6) $IRF_{VAR}(t, s, \boldsymbol{d}) = \boldsymbol{A}_s \boldsymbol{d}$ where $\boldsymbol{A}_s = \boldsymbol{\Phi}_{\mathbf{1}} \boldsymbol{A}_{s-1} + \boldsymbol{\Phi}_{\mathbf{2}} \boldsymbol{A}_{s-2} + \cdots + \boldsymbol{\Phi}_{\boldsymbol{P}} \boldsymbol{A}_{s-P}$,

where $\boldsymbol{A}_0$ equals the identity matrix and $\boldsymbol{A}_i$ equals 0 for $i < 0$. In the example with only one lag, only $\boldsymbol{\Phi}_{\boldsymbol{l}}$ for $l = 1$ is required. Calculation of standard errors for the VAR based IRF is complicated by the fact that the IRF is based on iterative forecasting with formulae for them being derived in e.g. Lütkepohl (1990).

In contrast to VARs, Local Projections perform regressions of the endogenous vector $\boldsymbol{y}_t$ on its own lags for each prediction horizon separately. Starting with a one period-ahead prediction, VARs and Local *Linear* Projections (LLP) estimate the same equation (W5) and provide the same impulse response estimate for *this horizon*.[15] Predicting *s* periods ahead, the LLP approach deviates from the VAR model by regressing the vector of endogenous variables at

[14] Parameter coefficients are not reported separately for dynamic effects because the "overall dynamic effect" subsumes too many parameters for straightforward interpretation (one for each forecasting horizon). Instead, the VAR literature and the LP literature use IRFs for interpretation. IRFs inform graphically about periods in which the dynamic effect is significant by including confidence intervals. If the confidence interval does not contain 0 in a specific period, the IRF is significant in that period. IRFs also inform about the effect size in each period.
[15] The equality only holds if the lag length for the LLPs at the first step-ahead (*s*=1) is chosen to be the same as the lag length for the VAR. We follow the majority of empirical papers (e.g., Auerbach and Gorodnichenko 2012; Tenreyro. and Thwaites 2016) and also use the VAR lag length for the LPs.

t+s steps ahead on the lagged variables for each horizon s=0,1,…,h:[16]

(W7) $$\boldsymbol{y_{t+s}} = \boldsymbol{\alpha_{LLP,s}} + \boldsymbol{B_{LLP,s+1,1}}\boldsymbol{y_{t-1}} + \cdots + \boldsymbol{B_{LLP,s+1,P}}\boldsymbol{y_{t-P}} + v_{LLP,st},$$

where $\boldsymbol{\alpha_{LLP,s}}$ and $\boldsymbol{B_{LLP,s+1,p}}$ are now new parameter vectors and matrices to be estimated.

The IRF for the impact of a shock $\boldsymbol{d}$ in time t on the endogenous variables in horizon t+s is:

(W8) $$IRF_{LLP}(t, s, \boldsymbol{d}) = \boldsymbol{B_{LLP,s,1}}\boldsymbol{d},$$

with the normalization $\boldsymbol{B_{LLP,0,1}} = \boldsymbol{I}.$

Thus, the key difference between the VAR in (W5) versus the LLP in (W7) is that, while the VAR only estimates one equation to obtain forecasts for all horizons, the LLP approach uses a collection of regressions, one for each horizon. Unlike the VAR-based IRF in (W6) that uses a recursive formula to forecast how the shock at time t perpetuates into the future (i.e., *iterated forecasts*), the LP-based IRFs in (W8) directly link the shock at t to the forecast s periods ahead based on the estimates of the $\boldsymbol{B_{LLP,s,1}}$ matrix (i.e., *direct forecast* for each horizon) that are obtained via univariate regression on each of the endogenous variables separately. Thus, forecasting errors are no longer accumulated over the forecasting period and standard errors for the LLP based IRF for the impact of a shock $\boldsymbol{d}$ on endogenous variable j can be simply calculated as $\boldsymbol{d}'\boldsymbol{\hat{\Sigma}^{j}_{LLP,s,1}}\boldsymbol{d}$ with $\boldsymbol{\hat{\Sigma}^{j}_{LLP,s,1}}$ the estimated heteroscedasticity and autocorrelation robust (HAC) variance covariance matrix of the j-th row of $\boldsymbol{B_{LLP,s,1}}$.

We note that the LLP-based IRFs in (W8) do not depend on the values of the endogenous variables, and that they are still symmetrical and linear in $\boldsymbol{d}$. To overcome these restrictions, Jordà (2005) also offers Local *Cubic* Projections (LCP), which add quadratic and cubic terms to

[16] Note that while the error terms in Local Projections are usually assumed to be normally distributed, this is not a necessary assumption (Jordà 2005).

(W7)[17]. To predict *s* periods ahead, the LCP approach regresses the vector of endogenous variables at *t*+1 on the lagged variables and their squared and cubic versions:

(W9) $$\boldsymbol{y}_{t+s} = \boldsymbol{\alpha}_{LCP,s} + \boldsymbol{B}_{LCP,s+1,1}\, \boldsymbol{y}_{t-1} + \boldsymbol{Q}_{LCP,s+1,1}\, \boldsymbol{y}_{t-1}^{2} + \boldsymbol{C}_{LCP,s+1,1}\boldsymbol{y}_{t-1}^{3} + \boldsymbol{B}_{LCP,s+1,2}\, \boldsymbol{y}_{t-2} + \cdots + \boldsymbol{B}_{LCP,s+1,P}\, \boldsymbol{y}_{t-P} + \boldsymbol{v}_{LCP,s,t}.$$ [18]

For the LCP, the IRF for a s-step ahead forecast can then be calculated as (Jordà 2005):

(W10) $$IRF_{LCP}(t,s,\boldsymbol{d}) = \boldsymbol{B}_{LCP,s,1}\boldsymbol{d} + \boldsymbol{Q}_{LCP,s,1}(2\cdot\, \boldsymbol{y}_{t-1}{}^{\circ}\boldsymbol{d} + \boldsymbol{d}^{2}) + \boldsymbol{C}_{LCP,s,1}(3\cdot\, \boldsymbol{y}_{t-1}^{2}{}^{\circ}\boldsymbol{d} + 3\cdot\, \boldsymbol{y}_{t-1}{}^{\circ}\boldsymbol{d}^{2} + \boldsymbol{d}^{3}),$$

where °, ², and ³, denote the respective Hadamard (element-by-element) products, squares and cubes of the vectors, and the normalizations with the normalization $\boldsymbol{B}_{LCP,0,1} = \boldsymbol{I}$, $\boldsymbol{Q}_{LCP,0,1} = \boldsymbol{0}$, and $\boldsymbol{C}_{LCP,0,1} = \boldsymbol{0}$. Importantly, the squared and cubic terms in (W9) do not have a substantive interpretation by themselves, but they make the *s*-period forecast at period *t* for the IRF_{LCP} depend on values of the endogenous variables stacked in vector $\boldsymbol{y}$ in period *t-1*, as shown in (W10). This creates history dependence and allows studying dynamic interaction effects. The quadratic ($\boldsymbol{d}^2$) and cubic ($\boldsymbol{d}^3$) terms in (W10) allow for nonlinearity: a *k*-times sized shock in investment is no longer restricted to cause a *k*-times sized effect of a unit investment shock. The quadratic and cubic terms also allow for asymmetry: a positive one standard deviation shock does not necessarily have the exact mirror effect of a negative shock of the same size. Estimation is carried out via univariate regression for each endogenous variable separately. Standard errors for the LCP based IRF are calculated for any shock $\boldsymbol{d}$ and any impacted endogenous variable *j* as

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[17] We note that other types of local projections have been proposed in the literature to enable more flexibility of the IRFs, yet these require–similar to the VAR-X extensions–a priori hypothesizing about these possible effects so that they can be incorporated in the model (e.g., Barnichon and Matthes 2018, Barnichon, Debortoli and Matthes 2021).

[18] In line with Jordà (2005, footnote 6), we restrict nonlinearities to the one-period lagged terms alone. In practice, if degrees of freedom are not a consideration, they can be extended to the remaining lags, although the gain of doing so is probably small. We also note that in the estimation we follow Jordà's original code and mean center the endogenous variables on the right hand side of the equation.

$\boldsymbol{\lambda}'\widehat{\boldsymbol{\Sigma}}^{\boldsymbol{j}}_{\boldsymbol{LCP,s,1}}\boldsymbol{\lambda}$ with $\widehat{\boldsymbol{\Sigma}}^{\boldsymbol{j}}_{\boldsymbol{LCP,s,1}}$ the estimated heteroscedasticity and autocorrelation robust (HAC) variance covariance matrix of the coefficients pertaining to the *j*-the rows of $B_{LCP,s,1}$, $\boldsymbol{Q_{LCP,s,1}}$ and $\boldsymbol{C_{LCP,s,1}}$, and $\boldsymbol{\lambda} = (\boldsymbol{d}, 2\boldsymbol{y}_{t-1}{\circ}\boldsymbol{d} + \boldsymbol{d}^2, 3\boldsymbol{y}_{t-1}^2{\circ}\boldsymbol{d} + 3\boldsymbol{y}_{t-1}{\circ}\boldsymbol{d}^2 + \boldsymbol{d}^3)'$.[19]

LCPs, unlike VAR models, allow for the exploration of dynamic interactions, asymmetries and nonlinearities without prior theoretical knowledge – they account for them by default. The quadratic and cubic terms in the LCPs imply that dynamic asymmetries and nonlinearities are automatically accounted for as is clear from the expression of the IRFs (see equation (W10)). It is a matter of empirical testing whether these effects are in fact significant. The analytical expressions of the standard errors of the LCP IRFs enable researchers to calculate the standard error of IRF differences at different histories. In addition, to compare the IRFs resulting from two shock sizes $\boldsymbol{d_1}$ and $\boldsymbol{d_2}$, the researcher can use the following equation

(W11) $$IRF_{LCP}(t,s,\boldsymbol{d_1}) - IRF_{LCP}(t,s,\boldsymbol{d_2}) = \boldsymbol{B_{LCP,s,1}}(\boldsymbol{d_1}-\boldsymbol{d_2}) + \boldsymbol{Q_{LCP,s,1}}\left(\boldsymbol{2}\cdot \boldsymbol{y_{t-1}}{\circ}(\boldsymbol{d_1}-\boldsymbol{d_2}) + \boldsymbol{d_1^2} - \boldsymbol{d_2^2}\right) + \boldsymbol{C_{LCP,s,1}}\left(\boldsymbol{3}\cdot \boldsymbol{y_{t-1}^2}{\circ}(\boldsymbol{d_1}-\boldsymbol{d_2}) + \boldsymbol{3}\cdot \boldsymbol{y_{t-1}}{\circ}\boldsymbol{d_1^2} + \boldsymbol{d_1^3} - \boldsymbol{3}\cdot \boldsymbol{y_{t-1}}{\circ}\boldsymbol{d_2^2} - \boldsymbol{d_2^3}\right),$$

with standard errors for the difference in endogenous variable *j* equal to $\boldsymbol{\lambda_{dif}}'\widehat{\boldsymbol{\Sigma}}^{\boldsymbol{j}}_{\boldsymbol{LCP,s,1}}\boldsymbol{\lambda_{dif}}$ with

$$\boldsymbol{\lambda_{dif}} = \left(\boldsymbol{d_1}-\boldsymbol{d_2}, \boldsymbol{2}\cdot \boldsymbol{y_t}{\circ}(\boldsymbol{d_1}-\boldsymbol{d_2}) + \boldsymbol{d_1^2} - \boldsymbol{d_2^2}, \boldsymbol{3}\cdot \boldsymbol{y_t^2}{\circ}(\boldsymbol{d_1}-\boldsymbol{d_2}) + \boldsymbol{3}\cdot \boldsymbol{y_t}{\circ}\boldsymbol{d_1^2} + \boldsymbol{d_1^3} - \boldsymbol{3}\cdot \boldsymbol{y_t}{\circ}\boldsymbol{d_2^2} - \boldsymbol{d_2^3}\right).'$$

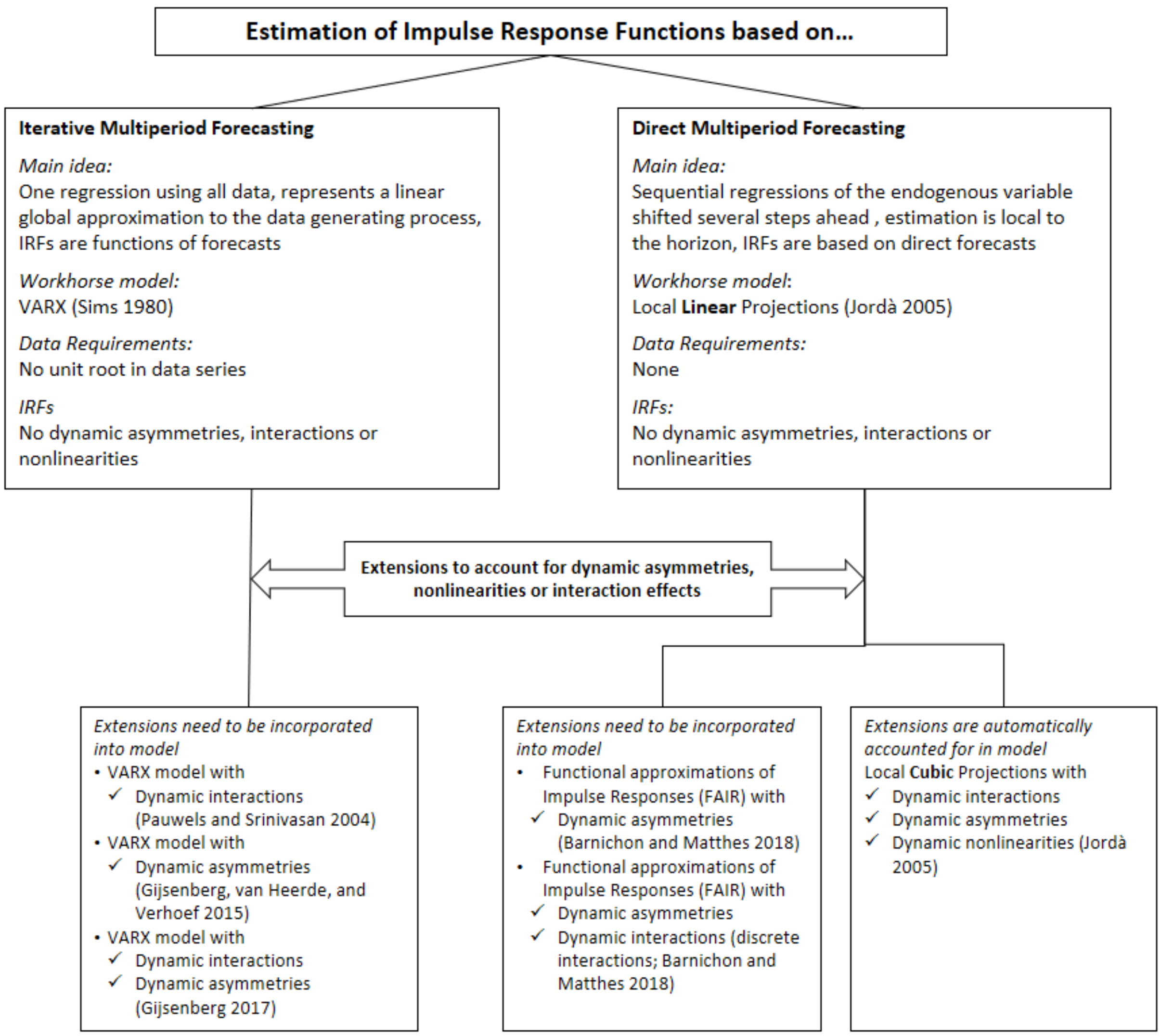
We note that this flexibility of LCPs is in contrast to the attempts to incorporate interactions or asymmetries in VARs (e.g., Gijsenberg, Van Heerde, and Verhoef 2015; Gijsenberg 2017; Luo, Raithel, and Wiles 2013; Pauwels and Srinivasan 2004), which all require the formulation of case-specific extensions and functional forms based on theory. While such theory-development and subsequent testing is certainly good practice, it also forces the empirical model into the frame implied by its theoretical counterpart. Further, such a formulation also can be hard to establish particularly when the phenomena under investigation are not yet sufficiently

[19] LPs also allow for Forecast Error Variance Decomposition, please see Gorodnichenko and Lee (2017).

backed by theory as it is the case here (Lehmann 2020).

Figure E.1 shows extensions of the two main approaches to derive IRFs (iterative multiperiod forecasting and direct multiperiod forecasting) to account for dynamic interactions, dynamic asymmetries and dynamic nonlinearities. Importantly, LCPs automatically include all three extensions, which makes LCPs particularly interesting in our context.

Figure E.1: Consideration of Interactions, Asymmetries, and Nonlinearities in Time-Series



Comparison of VARs and LPs

We now elaborate on the choice between VARs and LPs in general. The main difference is that VARs obtain iterative multiperiod forecasting based on one global approximation of the data generation process, while LPs employ direct multiperiod forecasting. Conventional wisdom on the performance of VAR versus LPs holds that VAR models are more efficient, while LPs are more robust to model misspecification (e.g., Li, Plagborg-Møller and Wolf 2021). The literature adds nuance to this tradeoff by identifying three potential boundary conditions.

Model misspecification. Jordà (2005) justified the introduction of LPs by arguing that any misspecification of the VAR, e.g., due to wrong variable or lag length selection, leads to errors that are compounded in its IRFs. LPs instead "do not require specification and estimation of the unknown true multivariate dynamic system itself" (Jordà 2005, p. 162), thus offering more flexibility in adapting to the underlying data. Using simulations, Jordà (2005, p. 166) shows that IRFs based on LPs outperform IRFs based on VARs when the latter are misspecified and suggests that "even when the true underlying model is a VAR, unrestricted local projections experience small efficiency losses". Chevillon and Hendry (2005) show that LPs can also prove either more efficient asymptotically, or more precise in finite samples—all depending on how misspecified the VAR is. We add that model misspecification is more likely when a phenomenon of interest is not backed by strong theory and prior findings. This implies that LPs may especially have an advantage over VARs when the empirical examination is explorative.

Data requirements. The question whether the data requirements are larger for LPs than for a VAR is currently unresolved (e.g., Brugnolini 2018; Killian and Kim 2011). In fact, LLPs and VARs estimate the same IRFs *in the population* when the data is weakly stationary and the lag structures in the two specifications are *unrestricted* (Plagborg-Møller and Wolf 2021).

However, population data are usually not available and lag structures tend to be restricted, which make these theoretical results less useful to guiding a choice in a particular application. One risk for VARs is that errors associated with the estimates compound in the IRFs. This results in local projections potentially outperforming VAR models in finite samples (see also Chevillon and Hendry 2005). On the other hand, local projections involve the estimation of a much larger number of parameters and are prone to sampling error (Stock and Watson 2011, p. 648). In sum, while LPs require the estimation of more parameters than VARs, there are no uniform guidelines regarding sample sizes favoring one approach over the other.

Reassuringly, as shown in the simulation study below, for realistic sample sizes and reasonable numbers of endogenous variables, LCPs perform well and are able to replicate the true IRFs. This holds even while the LCPs do not use the same lag length with which the data were generated and even when the IRFs are deliberately extended with dynamic nonlinearities, dynamic asymmetries and dynamic interactions.

Non-stationarity. In contrast to VARs, LPs are agnostic about the specification of the dynamic system and do not assume or require that the system is stationary and can deal with highly persistent data (Olea and Plagborg-Møller 2021).[20] The reason is that in local projections every horizon is estimated separately leading to a time-specific transition matrix. In contrast, in VARs the effect of the shock gets multiplied with a transition matrix that has been multiplied by itself several times. Thus, whereas in VARs an eigenvalue larger than 1 (unit root) means that any temporary shock triggers an exploding effect, in LPs the effect in horizon s is independent of the size of the effect in horizon s-1. As such, while stability of the system is important for the VAR model in equation (W5), it is irrelevant for the LLP and LCP equations (W7) and (W9),

[20] Olea and Plagborg-Møller (2021) suggest to augment LPs via additional lags of the endogenous variable if the data exhibits unit roots.

respectively. We note that LPs share this desirable characteristic with other direct forecasting methods, which ignore unit roots and cointegration for the same reason as LLPs and LCPs, yet have been shown to perform very well in comparison to other models that account for cointegration restrictions (Jordà 2005; Lin and Tsay 1996). In conclusion, researchers usually recommend direct multi-step forecasting whenever the data exhibits either stochastic or deterministic non-stationarity (unit-root and breaks) as this leads to more robust estimates (Chevillon and Hendry 2005; Lin and Tsay 1996).

Conclusion. The above discussion suggests that it is very difficult to come to a general conclusion about the superiority of VAR over LP and vice versa. While the lower-order VAR models may be incorrectly specified and data series often have to be transformed to meet stationarity requirements, the literature suggests that the robustness of the direct multiperiod forecast offered by the LP approach is suitable for many empirical applications (Marcellino, Stock, and Watson 2006). The take-away is that the choice between iterative multiperiod forecasting (i.e., VAR) and direct multiperiod forecasting (i.e., LP) is an empirical one (Plagborg-Møller and Wolf 2021) and may be informed by hold-out fit, as we do in our paper.

We note that while estimating parameters separately for each horizon increases the flexibility of Local Projections, it also means that there is no connection between the predictions for different forecast horizons which can make impulse response functions look somewhat wiggly and possibly difficulty to defend. Barnichon and Brownlees (2019) recently proposed a spline based smoothing procedure to address this issue in the context of local linear projections. Furthermore, while local linear projections so far have been mainly estimated using frequentist approaches, recent work by Tanaka (2020) and Miranda-Agrippino and Ricco (2021) propose to estimate local linear projections within a Bayesian framework that allows for priors that introduce smoothness or prior information, respectively.

Simulation Study

We now provide simulation studies to investigate the performance of LCPs not only in our empirical setting, but also under different data generating processes.

Creating data based on a VAR-X with 10 lags. The parameters for the Monte Carlo simulation are based on the empirical data used in the paper. In order create realistic data, we first estimate a panel VAR-X model with 10 lags ("VAR10-X model") on our data and save the coefficients as well as the variance-covariance of the residuals. We select 10 lags (instead of the one lag used in the paper) because we want to be able to generate intricate dynamic patterns (leading to intricate IRFs) to see whether LCPs can replicate them even though LCPs are agnostic about the data generating mechanism (see also the first experiment in Jordà 2005). We then simulate 1,000 new datasets of the same size as the original data using the observed exogenous variables, the saved coefficients (irrespective of their significance) as well as multivariate normal error terms that have the same covariance as the saved variance-covariance matrix of the residuals. We use the first 10 observations per team to initiate the runs and discard them afterwards.

Next, we estimate the correctly specified VAR10-X as well as LCP with 1 lag and generate IRFs based on a unit shock $\boldsymbol{d}$ in each of the six endogenous variables.[21] The IRFs from the VAR10-X are the true IRFs model as they are based on the data generating mechanism, whereas the LCP are an approximation. Results of this simulation are depicted in Figure E.2. This figure shows the mean of the VAR10-X IRFs, i.e., the IRFs of the correctly specified model, as well as the associated 95% Monte Carlo confidence intervals for 7 horizons. It also

[21] We use unit shocks rather than GIRF sized shocks in the simulations to ensure that the size of the shock is the same and the difference between IRFs is not due to differences in shock size.

depicts the mean of the LCP IRFs, which for all variable combinations lie within the 95% confidence interval of the correctly specified IRFs, and in almost all combinations is very close to this IRF. As such we conclude that the LCP approach is very well able to capture patterns of the true impulse responses for simulated data sets that are similar to our empirical data.

Simulations with varying data conditions and flexible dynamic effects. In the following set of simulations we again first estimate a panel VAR-X model with 10 lags and save the coefficients as well as the variance-covariance of the residuals. We then again simulate 1,000 new datasets using the saved coefficients pertaining to the lags $\boldsymbol{\Phi_1}$, …, $\boldsymbol{\Phi_{10}}$ (irrespective of their significance) as well as multivariate normal error terms $\boldsymbol{v}_t$ that have the same covariance as the saved variance-covariance matrix of the residuals to obtain reasonable effects, but we do not use the exogenous variables (and no panel structure) as reproduction of the data is not the focus of this study. Instead, we vary the number of endogenous variables (*k*=2,4,6)[22] as well as the number of different observations (*n*=100,250,500,1000,2000). We label the VAR model with 10 lags but without exogenous variables the VAR10 model.

We run five different sets of simulations. First, we just use a VAR10 to generate the data: $y_t = \boldsymbol{\Phi_1}\, \boldsymbol{y_{t-1}} + \boldsymbol{\Phi_{10}} \boldsymbol{y_{t-10}} + \boldsymbol{v}_t$. Second, we use a VAR10 and additionally add *nonlinearities*: $y_t = \boldsymbol{\Phi_1}\, \boldsymbol{y_{t-1}} + \boldsymbol{\Phi_{10}} \boldsymbol{y_{t-10}} - 0.25 \boldsymbol{\Phi_1}\, \boldsymbol{y_{t-1}} {}^\circ I(\boldsymbol{y_{t-1}} .> 0) + \boldsymbol{v}_t$, where ° denotes element wise multiplication, .> denotes element wise comparison and *I*(.) is an element wise dummy function that takes on the value 1 if the condition in parentheses is fulfilled and 0 else. The nonlinearity in this model comes from the coefficient –0.25 that is added to the lagged endogenous variable when it is positive. Third, we use a VAR10 and additionally add *asymmetries*: $y_t = \boldsymbol{\Phi_1}\, \boldsymbol{y_{t-1}} +$

[22] For *k*<6 we consider all possible combinations of the *k* endogenous variables and use only their respective entries in $\boldsymbol{\Phi_1}$ in the simulations.

$\boldsymbol{\Phi}_{\mathbf{10}} \boldsymbol{y}_{\boldsymbol{t-10}} - 0.25\boldsymbol{\Phi}_{\mathbf{1}}\, \boldsymbol{y}_{\boldsymbol{t-1}} \circ I(\boldsymbol{y}_{\boldsymbol{t-1}} .> \boldsymbol{y}_{\boldsymbol{t-1}}) + \boldsymbol{v}_t$. The asymmetry in this model comes from the coefficient –0.25 that multiplies the first-order autoregressive matrix $\boldsymbol{\Phi}_{\mathbf{1}}$ if the endogenous variable went up $(\boldsymbol{y}_{\boldsymbol{t-1}} .> \boldsymbol{y}_{\boldsymbol{t-1}})$. Fourth, we use a VAR10 and additionally add *interactions*: $y_t = \boldsymbol{\Phi}_{\mathbf{1}}\, \boldsymbol{y}_{\boldsymbol{t-1}} + \boldsymbol{\Phi}_{\mathbf{10}} \boldsymbol{y}_{\boldsymbol{t-10}} - 0.25\boldsymbol{\Phi}_{\mathbf{1}}\, [\mathbf{1}, .] \boldsymbol{y}_{\mathbf{1},\boldsymbol{t-1}} \circ \boldsymbol{y}_{\mathbf{2},\boldsymbol{t-1}} + \boldsymbol{v}_t$, where $\boldsymbol{\Phi}_{\mathbf{1}}\, [\mathbf{1}, .]$ is the first row of $\boldsymbol{\Phi}_{\mathbf{1}}$. Fifth, we use a VAR10 and additionally add *nonlinearities, asymmetries and interactions*: $y_t = \boldsymbol{\Phi}_{\mathbf{1}}\, \boldsymbol{y}_{\boldsymbol{t-1}} + \boldsymbol{\Phi}_{\mathbf{10}} \boldsymbol{y}_{\boldsymbol{t-10}} - 0.25\boldsymbol{\Phi}_{\mathbf{1}}\, [\mathbf{1}, .] \boldsymbol{y}_{\mathbf{1},\boldsymbol{t-1}} \circ \boldsymbol{y}_{\mathbf{2},\boldsymbol{t-1}} - 0.25\boldsymbol{\Phi}_{\mathbf{1}}\, \boldsymbol{y}_{\boldsymbol{t-1}} \circ (\boldsymbol{y}_{\boldsymbol{t-1}} .> \boldsymbol{y}_{\boldsymbol{t-1}}) - 0.25\boldsymbol{\Phi}_{\mathbf{1}}\, \boldsymbol{y}_{\boldsymbol{t-1}} \circ (\boldsymbol{y}_{\boldsymbol{t-1}} .> 0) + \boldsymbol{v}_t$.

In all sets of simulations, we estimate the correctly specified model as well as the LCPs. We then compare the IRFs based on the correctly specified model with the IRFs produced by the LCP using unit shocks $\boldsymbol{d}$ for seven horizons. For simulation set 1, the IRF can simply be calculated using the usual VAR IRF equation presented in the paper. For the other simulation sets we obtain the impulse response in horizon *s* by calculating the difference between the values of y_{t+s} when setting $y_t = \boldsymbol{d}$ versus $y_t = \mathbf{0}$ (and assuming $y_{t-p} = 0$ for all *p*).

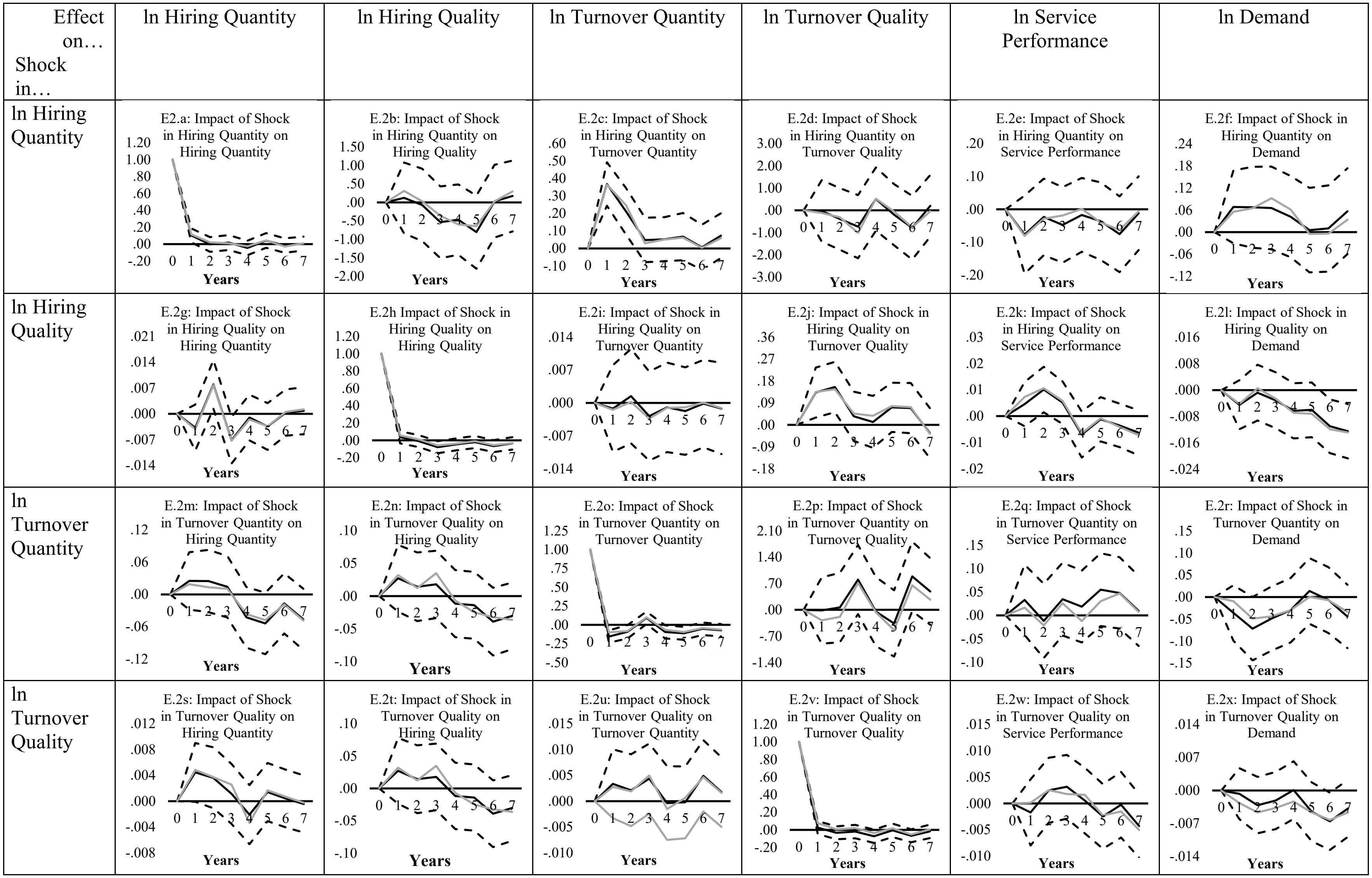
To measure the performance of the LCP under these different scenarios, we consider the squared deviation (SE) of LCP IRF from the IRF of the correctly specified model. We further measure bias as the absolute deviation between the LCP IRF and the IRF of the correctly specified model, expressed in terms of number of standard errors of the LCP IRF and denote this the statistic t-bias (Park and Gupta 2012). We thus obtain a t-bias for each of the horizons in each simulation. If the t-bias is smaller than 1.96 (corresponding to the 95% confidence interval), we can infer that the IRF in this particular horizon is consistent (see also Park and Gupta 2012).

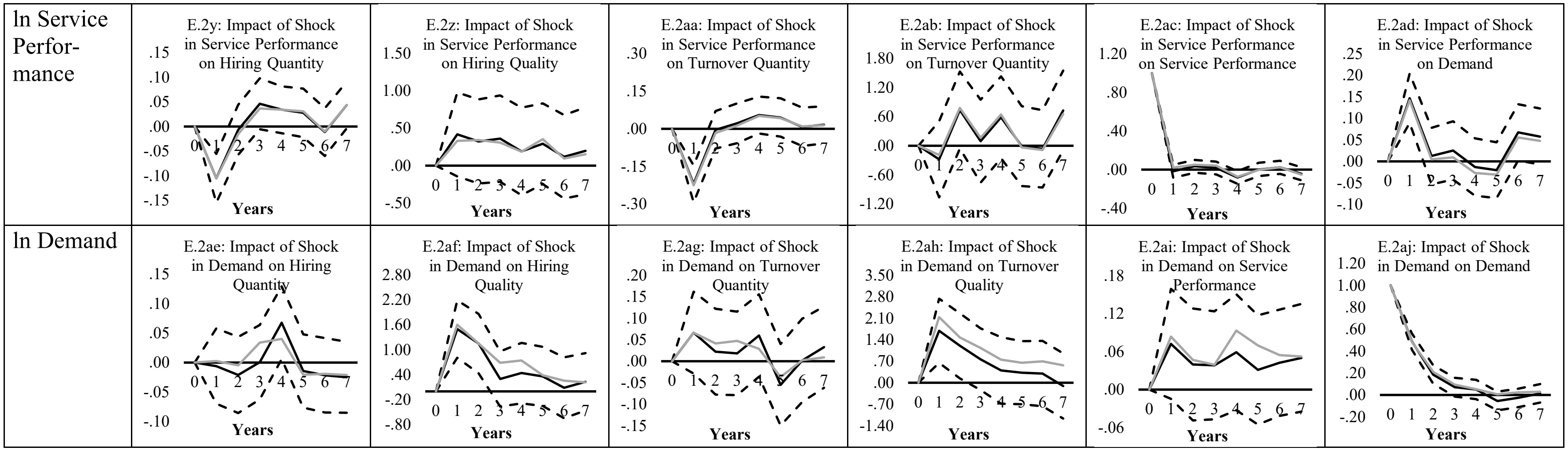
Results for the different simulation sets are reported in Table E.1. The results show that irrespective of the number of observations or number of endogenous variables used, the median t-bias is well below 1.96 and the share of simulations that have a t-bias above 1.96 lies between

89% and 97%. This suggests that LCPs provide unbiased IRFs even when the data generating process exhibits flexible dynamic effects. We also note that the performance of the LCPs across these measures as well as the median SE improves with larger sample size and fewer endogenous variables (as one would expect), and that only in the cell with the most challenging scenario (simulations with all flexible effects at the same time, k=6, n=100), the LCPs seem to struggle somewhat to recover the IRFs of the data generating process. In all other 14 cells, LCPs perform more than adequately, including in the cell closest to our empirical data (k=6, n=1,000).

In sum, these simulations show that across a wide variety of conditions, LCPs are robust and the estimated IRFs are very close to the true IRFs. Even though the LCPs use just one lag while the data were generated with 10 lags, and even though the IRFs were extended with dynamic nonlinearities, dynamic asymmetries and dynamic interactions, LCPs' flexible functional form allows it to capture the true IRFs.

Figure E.2: Comparison of LCP IRFs with IRFs from VAR10 based on Empirical Data





Notes: — VAR-X mean, — LCP mean, --- VAR-X 95% CI. The y-axis reports effect of unit sized shocks.

Table E.1: Performance Statistics for LCPs under different Simulation Scenarios

	VAR10			VAR10 with Nonlinearity			VAR10 with Asymmetry			VAR10 with Interactions			VAR10 with Nonlinearities, Asymmetries and Interactions		
	k=2	*k=4*	*k=6*	*k=2*	*k=4*	*k=6*	*k=2*	*k=4*	*k=6*	*k=2*	*k=4*	*k=6*	*k=2*	*k=4*	*k=6*
median t-bias															
n=100	.713	.694	.707	.720	.750	.955	.731	.739	.883	.705	.691	.715	.731	.817	1.568
n=250	.665	.620	.577	.665	.635	.609	.673	.632	.600	.660	.616	.580	.669	.651	.635
n=500	.652	.605	.553	.646	.618	.574	.655	.614	.567	.643	.601	.557	.648	.631	.593
n=1000	.656	.609	.557	.647	.624	.577	.655	.616	.567	.648	.606	.560	.656	.637	.600
n=2000	.668	.629	.578	.658	.645	.596	.662	.634	.582	.659	.627	.584	.679	.663	.627
median SE															
n=100	.030	.033	.043	.033	.041	.082	.032	.038	.069	.032	.034	.043	.035	.050	.218
n=250	.012	.011	.011	.012	.013	.013	.012	.012	.012	.012	.012	.012	.013	.013	.014
n=500	.006	.006	.005	.006	.007	.006	.006	.006	.006	.006	.006	.005	.006	.007	.006
n=1000	.003	.003	.003	.003	.004	.003	.003	.003	.003	.003	.003	.003	.003	.004	.003
n=2000	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002
% t-bias<1.96															
n=100	89.1	91.3	92.1	89.3	89.2	80.2	88.3	89.5	83.6	89.8	91.6	91.5	89.3	86.2	58.2
n=250	90.9	94.0	96.4	91.5	93.7	95.6	90.7	93.6	95.8	91.3	94.3	96.3	91.7	93.4	94.7
n=500	91.6	94.4	97.0	92.7	94.3	96.6	91.8	94.3	96.8	92.3	94.8	96.9	93.0	94.2	96.0
n=1000	91.5	94.2	96.9	92.9	94.1	96.6	92.0	94.2	96.8	92.0	94.6	96.8	93.0	93.9	95.9
n=2000	91.0	93.4	96.2	92.7	93.4	95.9	92.0	93.6	96.4	91.4	93.6	96.0	92.5	92.9	95.0

Notes: *k* is the number of endogenous variables, *n* the number of observations. % t-bias<1.96 provides the share of simulations in which the t-bias statistic is smaller than 1.96. We report median rather than average values as simulations involving nonlinear terms can generate extreme values which distort the average (Lütkepohl 2000).

WEB APPENDIX F: PARAMETER ESTIMATES BASED ON LCP

Table F.1: LCP, Horizon s = 0

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	**.158**	**.089**	-.084	**.655**	-.272	-.791
Lag ln Demand	**.608**	**.102**	-.091	**1.193**	.033	**1.770**
Lag ln Hiring Quantity	.047	-.078	**.083**	.197	**.361**	-.257
Lag ln Hiring Quality	-.008	.009	.003	**.190**	-.001	**.134**
Lag ln Turnover Quantity	.035	-.070	.063	.130	-.026	.097
Lag ln Turnover Quality	.005	.004	-.001	-.004	.002	.078
(Lag ln Demand)^2	.040	**.060**	.005	**.877**	-.043	.631
(Lag ln Service Performance)^2	.001	**.139**	.113	.577	.116	-.911
(Lag ln Hiring Quantity)^2	**.089**	-.035	**.137**	-.212	.016	.309
(Lag ln Hiring Quality)^2	-.001	-.001	.001	-.004	.001	.010
(Lag ln Turnover Quantity)^2	-.025	.056	-.098	-.407	-.042	.351
(Lag ln Turnover Quality)^2	.000	.000	.001	**.017**	.000	.014
(Lag ln Demand)^3	-.024	**.033**	**.035**	**.283**	.006	-.045
(Lag ln Service Performance)^3	-.017	.029	.042	.186	**.067**	-.140
(Lag ln Hiring Quantity)^3	**.077**	-.002	**.167**	-.352	**.063**	.081
(Lag ln Hiring Quality)^3	.000	.000	.000	-.002	.000	.000
(Lag ln Turnover Quantity)^3	-.024	**.078**	-.028	-.161	.042	-.037
(Lag ln Turnover Quality)^3	.000	.000	.000	.001	.000	.001
Ln Team Age	.034	-.046	**.368**	1.090	**.242**	1.101
Three-league System	**.063**	-.070	.029	.119	.009	-.033
League 1	**1.122**	-1.222	-.135	**7.588**	-.372	4.103
League 2	**.767**	-.865	-.063	**5.963**	-.290	4.014
League3	**.380**	-.519	-.201	3.363	-.211	2.602
League 4	.226	-.318	-.188	2.247	-.198	2.419
League 5	.002	.128	-.153	.353	-.113	1.304
Three Points	.053	-.017	**.162**	.046	.024	.843
Euro Introduction	**.096**	-.009	-.006	-.178	.069	-.484
German Reunification	**.151**	-.040	.045	**2.573**	.042	**1.761**

National Team Wins	**.065**	.008	.022	.338	.017	.192
ln Population	.008	-.272	-.615	-.181	-.405	-.105
1.FC Kaiserslautern	2.855	**8.102**	**8.088**	-1.248	**6.424**	-1.157
1. FC Cologne	2.522	**8.714**	**9.416**	-.491	**7.336**	.867
1. FC Nuremberg	2.611	**8.392**	**9.156**	-1.771	**7.146**	-.308
1. FC Saarbruecken	1.878	**7.863**	**8.584**	-6.763	**6.649**	-5.230
TSV 1860 Munich	2.129	**8.544**	**9.649**	-2.589	**7.377**	-1.976
Arminia Bielefeld	2.712	**8.130**	**8.925**	-3.923	**6.912**	-2.625
Bayer 04 Leverkusen	2.855	**8.418**	**8.411**	.483	**6.751**	1.173
FC Bayern Munich	2.681	**9.390**	**9.311**	1.491	**7.255**	2.409
Borussia Dortmund	2.828	**8.868**	**8.922**	-.406	**7.023**	1.711
Borussia Monchengladbach	2.774	**8.407**	**8.506**	-1.219	**6.721**	1.549
Eintracht Braunschweig	2.505	**8.020**	**8.586**	-5.024	**6.593**	-5.464
Eintracht Frankfurt	2.440	**8.577**	**9.306**	-2.023	**7.267**	-.543
FC St. Pauli	2.873	**8.563**	**9.821**	-3.018	**7.293**	-2.757
FSV Mainz 05	1.970	**8.260**	**9.263**	-3.847	**7.169**	-3.613
Fortuna Dusseldorf	2.208	**8.055**	**8.548**	-4.395	**6.676**	-2.946
Hamburger SV	2.543	**8.994**	**9.855**	.812	**7.660**	1.887
Hannover 96	2.095	**8.352**	**9.186**	-4.181	**7.186**	-2.805
FC Hansa Rostock	2.343	**7.872**	**8.371**	-4.916	**6.546**	-3.744
Hertha BSC Berlin	2.006	**8.952**	**1.190**	-2.670	**7.833**	-1.189
KFC Uerdingen 05	2.493	**8.178**	**8.665**	-3.850	**6.712**	-2.675
Karlsruher SC	1.668	**7.800**	**8.893**	-3.089	**6.915**	-3.123
MSV Duisburg	2.183	**8.269**	**9.097**	-4.508	**6.998**	-3.638
SC Freiburg	2.740	**8.116**	**8.662**	-3.094	**6.811**	-1.108
SV Darmstadt 98	2.663	**8.479**	**8.621**	-2.120	**6.825**	-.439
SV Waldhof Mannheim	2.216	**7.809**	**8.158**	-4.906	**6.434**	-3.167
FC Schalke 04	2.111	**8.384**	**1.010**	-5.179	**7.598**	-3.334
SpVgg Greuther Fuerth	2.007	**7.643**	**8.473**	-6.702	**6.548**	-5.317
SpVgg Unterhaching	2.262	**8.027**	**9.092**	-5.428	**7.051**	-4.523
VfB Stuttgart	2.520	**8.763**	**9.066**	-.012	**7.118**	1.296
VfL Bochum	2.715	**8.312**	**8.963**	-3.261	**6.974**	-1.583
VfL Osnabrueck	2.434	**7.828**	**8.598**	-5.216	**6.602**	-4.875
VfL Wolfsburg	2.137	**8.023**	**8.018**	-3.000	**6.215**	-3.288
SV Werder Bremen	2.717	**8.800**	**8.913**	-.096	**6.965**	.552
Model fit: R^2	.532	.662	.600	.469	.309	.867

Notes: Significant parameters ($p < .05$) in bold.

Table F.2: LCP, Horizon *s* = 1

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	.064	**.109**	-.033	**.649**	.042	**.851**
Lag ln Demand	**.343**	**.109**	-.066	**.679**	**.107**	**1.455**
Lag ln Hiring Quantity	.063	-.034	.027	.447	**.156**	.020
Lag ln Hiring Quality	.003	**.019**	.004	.079	.010	**.197**
Lag ln Turnover Quantity	.023	-.063	.053	-.378	.009	-.395
Lag ln Turnover Quality	-.001	.004	.002	-.005	-.008	-.027
(Lag ln Demand)^2	**.097**	**.085**	.017	**1.156**	-.052	.562
(Lag ln Service Performance)^2	.068	.012	.042	.735	-.113	-2.355
(Lag ln Hiring Quantity)^2	.052	.025	.000	-.333	.021	.926
(Lag ln Hiring Quality)^2	-.003	-.002	**.002**	.011	**.003**	.016
(Lag ln Turnover Quantity)^2	-.027	-.044	-.092	-.588	-.090	-.284
(Lag ln Turnover Quality)^2	.000	.000	.001	.005	.001	.005
(Lag ln Demand)^3	.018	.007	**.032**	**.350**	-.001	.035
(Lag ln Service Performance)^3	-.008	-.023	.028	.265	-.039	-.686
(Lag ln Hiring Quantity)^3	.041	.048	**.076**	-.394	**.113**	-.092
(Lag ln Hiring Quality)^3	.000	.000	.000	.000	.000	-.001
(Lag ln Turnover Quantity)^3	-.024	-.001	-.013	-.075	-.002	.042
(Lag ln Turnover Quality)^3	.000	.000	.000	.001	.000	**.003**
Ln Team Age	.116	-.018	**.407**	1.299	**.480**	**1.793**
Three-league System	.081	-.078	.034	.243	-.045	-.169
League 1	**1.595**	-1.182	-.259	**9.401**	-.638	4.736
League 2	**1.099**	-.860	-.116	**7.274**	-.405	4.618
League3	**.581**	-.548	-.234	4.014	-.312	2.795
League 4	.299	-.304	-.211	2.815	-.239	2.736
League 5	.086	.163	-.161	.621	-.122	1.732
Three Points	**.109**	-.054	**.169**	.222	.027	.806
Euro Introduction	**.138**	-.002	-.015	-.066	.008	-.596
German Reunification	**.179**	-.041	.022	**2.787**	-.028	**1.533**
National Team Wins	**.079**	.019	.018	.390	.025	.185
ln Population	-.160	-.287	-.499	-.325	-.448	1.683

1.FC Kaiserslautern	3.970	**8.167**	**6.759**	-1.804	**6.395**	-23.879
1. FC Cologne	4.014	**8.824**	**7.842**	-1.230	**7.423**	-26.005
1. FC Nuremberg	4.006	**8.494**	**7.618**	-2.264	**7.171**	-25.932
1. FC Saarbruecken	3.283	**8.005**	**7.132**	-7.112	**6.515**	-29.287
TSV 1860 Munich	3.794	**8.687**	**7.953**	-2.825	7.338	-29.212
Arminia Bielefeld	4.129	**8.259**	**7.441**	-4.716	**6.901**	-27.399
Bayer 04 Leverkusen	4.047	**8.512**	**7.047**	-.288	**6.897**	-21.998
FC Bayern Munich	4.204	**9.484**	**7.678**	.846	7.364	-24.876
Borussia Dortmund	4.209	**8.962**	**7.382**	-.923	7.085	-24.180
Borussia Monchengladbach	4.039	**8.499**	**7.065**	-2.242	**6.757**	-23.306
Eintracht Braunschweig	3.927	**8.158**	**7.085**	-5.454	6.466	-3.203
Eintracht Frankfurt	3.857	**8.673**	**7.740**	-2.728	**7.310**	-26.939
FC St. Pauli	4.641	**8.721**	**8.148**	-3.138	7.345	-3.442
FSV Mainz 05	3.476	**8.403**	**7.680**	-4.439	**7.144**	-29.556
Fortuna Dusseldorf	3.578	**8.181**	**7.090**	-5.317	**6.663**	-26.585
Hamburger SV	4.100	**9.100**	**8.210**	.087	**7.819**	-25.860
Hannover 96	3.531	**8.458**	**7.625**	-5.048	**7.159**	-28.465
FC Hansa Rostock	3.653	**8.046**	**6.991**	-5.580	6.458	-28.197
Hertha BSC Berlin	3.726	**9.083**	**8.397**	-3.052	7.896	-3.324
KFC Uerdingen 05	3.841	**8.289**	**7.210**	-4.429	6.680	-27.378
Karlsruher SC	3.072	**7.933**	**7.423**	-3.659	**6.887**	-27.264
MSV Duisburg	3.653	**8.379**	**7.521**	-5.197	6.915	-29.617
SC Freiburg	4.070	**8.239**	**7.219**	-3.772	**6.866**	-24.975
SV Darmstadt 98	3.944	**8.574**	**7.155**	-3.053	**6.807**	-25.030
SV Waldhof Mannheim	3.533	**7.939**	**6.772**	-5.404	**6.379**	-25.963
FC Schalke 04	3.830	**8.605**	**8.374**	-5.392	**7.764**	-3.112
SpVgg Greuther Fuerth	3.383	**7.808**	**7.077**	-7.078	**6.519**	-28.719
SpVgg Unterhaching	3.791	**8.176**	**7.628**	-5.747	**7.025**	-29.310
VfB Stuttgart	3.903	**8.851**	**7.550**	-.481	**7.213**	-24.823
VfL Bochum	4.100	**8.422**	**7.465**	-3.791	**7.015**	-26.751
VfL Osnabrueck	3.839	**7.986**	**7.144**	-5.533	**6.532**	-28.742
VfL Wolfsburg	3.395	**8.160**	**6.695**	-3.765	**6.287**	-26.069
SV Werder Bremen	4.093	**8.903**	**7.389**	-.765	7.053	-25.290
Model fit: R^2	.502	.660	.538	.483	.327	.831

Notes: Significant parameters ($p < .05$) in bold.

Table F.3: LCP, Horizon *s* = 2

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	.040	**.097**	-.020	.368	**.077**	.459
Lag ln Demand	**.218**	**.071**	-.017	**.643**	**.130**	**2.080**
Lag ln Hiring Quantity	.043	-.065	.009	-.378	.060	-.593
Lag ln Hiring Quality	.005	.010	-.011	.013	-.001	.119
Lag ln Turnover Quantity	.034	.037	.009	.564	.070	.387
Lag ln Turnover Quality	.003	.002	.009	.086	.009	.061
(Lag ln Demand)^2	**.150**	**.060**	**.066**	**1.332**	.037	**.862**
(Lag ln Service Performance)^2	-.094	-.083	-.022	-.587	-.012	-.505
(Lag ln Hiring Quantity)^2	.073	.047	.029	-.132	-.013	-.207
(Lag ln Hiring Quality)^2	-.003	-.001	.000	.007	.001	.000
(Lag ln Turnover Quantity)^2	-.049	-.041	-.052	-.205	-.021	.312
(Lag ln Turnover Quality)^2	-.001	.000	.001	.008	.000	.015
(Lag ln Demand)^3	**.041**	.006	**.033**	**.338**	.008	-.133
(Lag ln Service Performance)^3	-.044	-.048	.013	-.108	-.015	-.275
(Lag ln Hiring Quantity)^3	.069	.036	**.108**	-.030	**.098**	-.177
(Lag ln Hiring Quality)^3	.000	.000	.000	.000	.000	-.002
(Lag ln Turnover Quantity)^3	-.034	-.020	.008	-.225	.045	.225
(Lag ln Turnover Quality)^3	.000	.000	.000	-.002	.000	.001
Ln Team Age	.149	-.011	**.511**	.642	**.526**	1.866
Three-league System	.095	-.072	.008	.348	-.065	-.220
League 1	**1.887**	-1.005	-.216	**1.454**	-.573	4.830
League 2	**1.349**	-.712	-.075	**8.158**	-.354	4.501
League3	**.740**	-.442	-.208	**4.398**	-.310	2.285
League 4	.368	-.232	-.230	3.112	-.306	2.203
League 5	.137	.188	-.142	.997	-.138	1.077
Three Points	.119	-.039	**.150**	.363	-.006	.914
Euro Introduction	**.158**	-.016	-.023	.123	.005	-.729

German Reunification	**.209**	-.021	.032	**3.354**	.012	**1.912**
National Team Wins	.057	.011	-.008	.617	.010	.421
ln Population	-.166	-.238	-.526	.275	-.458	.957
1.FC Kaiserslautern	3.637	**7.391**	**6.674**	-8.362	6.276	-16.816
1. FC Cologne	3.680	**7.948**	7.805	-9.137	7.304	-17.224
1. FC Nuremberg	3.677	**7.653**	**7.577**	-9.559	7.069	-17.392
1. FC Saarbruecken	3.078	**7.246**	**7.095**	-13.055	6.481	-2.615
TSV 1860 Munich	3.527	**7.805**	7.943	-1.667	7.282	-19.523
Arminia Bielefeld	3.872	**7.447**	**7.433**	-11.544	6.863	-18.794
Bayer 04 Leverkusen	3.704	**7.732**	**6.993**	-7.289	6.795	-14.408
FC Bayern Munich	3.841	**8.585**	7.649	-7.401	7.247	-15.801
Borussia Dortmund	3.850	**8.109**	7.342	-8.617	6.986	-15.557
Borussia Monchengladbach	3.685	**7.671**	7.010	-9.305	6.647	-15.303
Eintracht Braunschweig	3.694	**7.359**	7.032	-11.569	6.414	-21.859
Eintracht Frankfurt	3.523	**7.809**	**7.709**	-1.147	7.214	-18.187
FC St. Pauli	4.408	**7.821**	8.191	-11.382	7.326	-2.802
FSV Mainz 05	3.220	**7.558**	**7.676**	-11.341	7.102	-2.634
Fortuna Dusseldorf	3.301	**7.396**	**7.025**	-12.152	6.580	-18.417
Hamburger SV	3.746	**8.174**	8.174	-8.188	7.678	-16.687
Hannover 96	3.219	**7.621**	**7.576**	-12.178	7.056	-19.834
FC Hansa Rostock	3.383	**7.226**	6.950	-12.195	6.414	-19.964
Hertha BSC Berlin	3.382	**8.169**	8.382	-11.473	7.773	-2.723
KFC Uerdingen 05	3.554	**7.479**	7.169	-11.085	6.628	-19.018
Karlsruher SC	2.837	**7.170**	**7.401**	-1.376	6.850	-19.001
MSV Duisburg	3.377	**7.533**	7.503	-12.145	6.866	-2.749
SC Freiburg	3.772	**7.445**	**7.211**	-1.846	6.792	-17.202
SV Darmstadt 98	3.607	**7.764**	7.094	-9.980	6.724	-17.167
SV Waldhof Mannheim	3.299	**7.189**	**6.695**	-11.686	6.296	-17.736
FC Schalke 04	3.619	**7.718**	**8.469**	-13.610	7.772	-2.498
SpVgg Greuther Fuerth	3.153	**7.043**	**7.048**	-13.034	6.481	-2.103
SpVgg Unterhaching	3.584	**7.356**	**7.639**	-12.544	7.050	-2.174
VfB Stuttgart	3.549	**7.986**	7.498	-8.209	7.090	-16.372
VfL Bochum	3.792	**7.587**	**7.467**	-1.910	6.954	-18.154
VfL Osnabrueck	3.608	**7.207**	**7.135**	-11.683	6.510	-2.003
VfL Wolfsburg	3.124	**7.363**	6.649	-1.772	6.219	-17.963
SV Werder Bremen	3.758	**8.045**	7.322	-8.540	6.922	-16.880
Model fit: R^2	.493	.656	.510	.470	.301	.823

Notes: Significant parameters ($p < .05$) in bold.

Table F.4: LCP, Horizon *s* = 3

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	-.024	-.032	.005	.162	.046	.517
Lag ln Demand	**.165**	**.100**	-.032	.583	**.084**	**1.961**
Lag ln Hiring Quantity	.029	-.034	-.032	-.525	.010	-.409
Lag ln Hiring Quality	.001	-.003	.004	.089	-.001	**.151**
Lag ln Turnover Quantity	.003	.012	.011	-.067	-.032	.214
Lag ln Turnover Quality	.001	-.002	.002	-.036	.000	-.072
(Lag ln Demand)^2	**.145**	.058	**.093**	**1.333**	.028	**1.117**
(Lag ln Service Performance)^2	-.081	-.052	-.002	-.039	.087	1.154
(Lag ln Hiring Quantity)^2	.074	.025	.004	-.707	-.082	-.827
(Lag ln Hiring Quality)^2	-.003	.001	-.001	-.002	.001	-.025
(Lag ln Turnover Quantity)^2	-.053	-.057	-.020	-.109	-.005	.222
(Lag ln Turnover Quality)^2	-.001	.000	.001	.002	.001	**.019**
(Lag ln Demand)^3	.037	-.004	**.054**	**.369**	.011	-.032
(Lag ln Service Performance)^3	-.028	-.028	.003	-.020	.027	.350
(Lag ln Hiring Quantity)^3	.066	.047	.062	-.157	**.095**	-.114
(Lag ln Hiring Quality)^3	.000	.000	.000	-.002	.000	-.004
(Lag ln Turnover Quantity)^3	-.024	-.051	.021	.178	.045	.059
(Lag ln Turnover Quality)^3	.000	.000	.000	.000	.000	**.003**
Ln Team Age	**.330**	-.023	**.708**	**2.239**	**.637**	**4.197**
Three-league System	.083	-.051	-.032	.110	-.044	-.663
League 1	**2.108**	-.912	-.245	**1.142**	-.475	**5.481**
League 2	**1.526**	-.648	-.087	**7.865**	-.283	**5.119**
League3	**.889**	-.384	-.221	**4.211**	-.248	2.583
League 4	.443	-.190	-.306	2.648	-.339	2.152
League 5	.170	.182	-.212	.376	-.168	.697
Three Points	**.135**	-.015	**.142**	.194	.025	.635
Euro Introduction	**.148**	-.010	-.041	.015	.033	-1.132

German Reunification	**.210**	.022	.003	**3.074**	.026	**1.523**
National Team Wins	.044	.009	-.003	.662	.017	.372
ln Population	-.371	-.443	-.774	-1.425	-.580	-1.382
1.FC Kaiserslautern	5.127	**9.643**	**8.858**	6.405	7.119	1.902
1. FC Cologne	5.641	**1.678**	**1.559**	9.474	8.441	6.957
1. FC Nuremberg	5.500	**1.240**	**1.167**	7.931	8.126	5.110
1. FC Saarbruecken	4.748	**9.633**	**9.489**	2.586	7.424	-.475
TSV 1860 Munich	5.580	**1.576**	**1.760**	8.794	8.443	5.826
Arminia Bielefeld	5.668	**9.933**	**9.969**	5.422	7.864	3.199
Bayer 04 Leverkusen	5.355	**1.093**	**9.397**	8.995	7.743	6.606
FC Bayern Munich	5.856	**11.370**	**1.478**	11.874	8.446	9.569
Borussia Dortmund	5.689	**1.723**	**9.965**	9.129	8.044	7.695
Borussia Monchengladbach	5.370	**1.120**	**9.435**	7.023	7.616	5.993
Eintracht Braunschweig	5.406	**9.781**	**9.478**	4.528	7.369	-.998
Eintracht Frankfurt	5.399	**1.443**	**1.377**	7.839	8.287	5.083
FC St. Pauli	6.601	**1.655**	**11.174**	9.088	8.609	5.554
FSV Mainz 05	5.125	**1.183**	**1.332**	6.445	8.167	2.459
Fortuna Dusseldorf	5.026	**9.759**	**9.467**	4.562	7.570	3.171
Hamburger SV	5.802	**11.008**	**11.107**	11.464	8.907	8.725
Hannover 96	5.063	**1.187**	**1.215**	5.416	8.119	3.234
FC Hansa Rostock	5.077	**9.632**	**9.370**	4.335	7.425	1.626
Hertha BSC Berlin	5.590	**11.131**	**11.456**	9.228	9.060	6.503
KFC Uerdingen 05	5.273	**9.949**	**9.622**	5.440	7.610	2.479
Karlsruher SC	4.630	**9.599**	**9.908**	6.419	7.870	2.822
MSV Duisburg	5.238	**1.115**	**1.106**	5.459	7.912	1.768
SC Freiburg	5.521	**9.840**	**9.693**	6.245	7.779	4.913
SV Darmstadt 98	5.289	**1.220**	**9.535**	6.746	7.677	4.249
SV Waldhof Mannheim	4.937	**9.488**	**8.990**	4.235	7.233	2.752
FC Schalke 04	5.834	**1.476**	**11.485**	7.274	9.055	7.044
SpVgg Greuther Fuerth	4.834	**9.408**	**9.419**	2.684	7.445	.178
SpVgg Unterhaching	5.427	**9.838**	**1.238**	4.885	8.180	2.724
VfB Stuttgart	5.395	**1.613**	**1.132**	9.581	8.151	6.676
VfL Bochum	5.603	**1.106**	**1.041**	6.505	7.988	4.375
VfL Osnabrueck	5.319	**9.576**	**9.527**	4.482	7.481	1.094
VfL Wolfsburg	4.765	**9.656**	**8.952**	5.820	7.194	3.022
SV Werder Bremen	5.582	**1.646**	**9.941**	9.272	7.975	6.224
Model fit: R^2	.476	.662	.476	.487	.293	.819

Notes: Significant parameters ($p < .05$) in bold

Table F.5: LCP, Horizon s = 4

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	.011	.052	.043	.565	.045	.465
Lag ln Demand	.083	**.073**	-.038	.540	.017	**.869**
Lag ln Hiring Quantity	-.070	-.059	.015	-.724	.045	-.321
Lag ln Hiring Quality	.003	.003	-.006	.059	.002	**.133**
Lag ln Turnover Quantity	.056	-.009	.012	.419	-.036	-.050
Lag ln Turnover Quality	-.003	-.012	.008	.082	.002	.078
(Lag ln Demand)^2	**.102**	**.064**	.058	**.875**	.052	**.919**
(Lag ln Service Performance)^2	-.117	-.085	.005	.062	-.032	.374
(Lag ln Hiring Quantity)^2	.072	-.052	.046	-.489	-.001	-.519
(Lag ln Hiring Quality)^2	-.002	.000	.000	-.011	.000	-.020
(Lag ln Turnover Quantity)^2	-.029	.002	-.041	-.454	.008	-.257
(Lag ln Turnover Quality)^2	-.001	.000	.001	-.004	.001	.002
(Lag ln Demand)^3	.033	.008	.026	.194	.032	.312
(Lag ln Service Performance)^3	-.040	-.032	-.001	-.035	-.014	.016
(Lag ln Hiring Quantity)^3	.091	.003	**.092**	-.121	.087	-.193
(Lag ln Hiring Quality)^3	.000	.000	.000	-.001	.000	-.002
(Lag ln Turnover Quantity)^3	-.022	.015	.006	-.207	.028	-.158
(Lag ln Turnover Quality)^3	.000	.000	.000	-.002	.000	.000
Ln Team Age	**.402**	-.026	**.675**	**2.980**	**.800**	**4.144**
Three-league System	.090	-.055	-.019	.120	-.074	-.298
League 1	**2.192**	-.916	-.217	**1.945**	-.374	**6.581**
League 2	**1.597**	-.654	-.067	**8.402**	-.185	**6.099**
League3	**.946**	-.379	-.188	**4.572**	-.198	3.258
League 4	.465	-.191	-.304	2.781	-.324	2.577
League 5	.178	.192	-.207	.486	-.138	1.292
Three Points	**.147**	-.026	**.142**	.017	-.004	.524
Euro Introduction	**.169**	.007	-.049	-.227	.012	-1.053
German Reunification	**.202**	.013	-.017	**2.855**	.019	**1.685**
National Team Wins	.053	.018	-.012	.551	.016	.339
ln Population	-.312	-.282	-.534	-1.828	-.766	-1.728

1.FC Kaiserslautern	4.070	**7.842**	6.238	7.979	**8.622**	5.297
1. FC Cologne	4.471	**8.497**	7.376	12.252	**1.356**	1.672
1. FC Nuremberg	4.366	**8.183**	7.176	1.486	**9.929**	8.985
1. FC Saarbruecken	3.656	**7.689**	6.683	5.203	**9.076**	3.363
TSV 1860 Munich	4.381	**8.380**	7.539	11.994	**1.400**	1.028
Arminia Bielefeld	4.556	**7.929**	7.022	8.425	**9.648**	7.289
Bayer 04 Leverkusen	4.304	**8.231**	6.614	1.920	**9.385**	9.951
FC Bayern Munich	4.663	**9.171**	7.219	14.337	**1.410**	13.267
Borussia Dortmund	4.527	**8.648**	6.918	11.355	**9.887**	11.235
Borussia Monchengladbach	4.262	**8.166**	6.561	9.355	**9.298**	9.330
Eintracht Braunschweig	4.315	**7.821**	6.595	7.664	**9.094**	3.374
Eintracht Frankfurt	4.233	**8.339**	7.284	1.536	**1.141**	8.761
FC St. Pauli	5.434	**8.401**	7.836	12.620	**1.714**	1.294
FSV Mainz 05	3.989	**8.083**	7.271	9.778	**1.046**	6.479
Fortuna Dusseldorf	4.000	**7.862**	6.638	7.640	**9.266**	7.306
Hamburger SV	4.584	**8.736**	7.774	13.972	**1.927**	12.765
Hannover 96	3.960	**8.133**	7.166	8.507	**9.958**	7.582
FC Hansa Rostock	3.962	**7.719**	6.527	6.825	**9.074**	5.458
Hertha BSC Berlin	4.341	**8.799**	7.976	12.967	**11.246**	11.562
KFC Uerdingen 05	4.160	**7.985**	6.716	8.238	**9.312**	6.617
Karlsruher SC	3.564	**7.632**	7.069	9.863	**9.610**	6.956
MSV Duisburg	4.102	**8.064**	7.047	8.421	**9.708**	5.877
SC Freiburg	4.459	**7.933**	6.850	8.818	**9.512**	8.596
SV Darmstadt 98	4.168	**8.279**	6.646	8.934	**9.372**	8.038
SV Waldhof Mannheim	3.949	**7.680**	6.294	7.088	**8.797**	6.524
FC Schalke 04	4.673	**8.240**	8.170	11.341	**11.171**	11.267
SpVgg Greuther Fuerth	3.805	**7.507**	6.675	5.571	**9.081**	3.945
SpVgg Unterhaching	4.329	**7.835**	7.325	8.034	**9.973**	6.686
VfB Stuttgart	4.237	**8.520**	7.066	11.725	**9.969**	1.174
VfL Bochum	4.473	**8.093**	7.057	9.274	**9.788**	8.231
VfL Osnabrueck	4.283	**7.662**	6.732	7.163	**9.139**	4.820
VfL Wolfsburg	3.762	**7.849**	6.297	8.876	**8.737**	7.177
SV Werder Bremen	4.420	**8.570**	6.897	11.292	**9.778**	1.025
Model fit: R^2	.462	.661	.437	.480	.295	.814

Notes: Significant parameters ($p < .05$) in bold.

Table F.6: LCP, Horizon *s* = 5

	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	.009	**.077**	-.001	.548	.035	.281
Lag ln Demand	**.110**	.038	-.010	.217	.040	**1.205**
Lag ln Hiring Quantity	-.084	-.061	-.060	.244	-.050	-.724
Lag ln Hiring Quality	-.011	-.003	.008	-.043	.005	.103
Lag ln Turnover Quantity	.084	.010	.011	.388	.028	**1.169**
Lag ln Turnover Quality	-.001	-.003	-.001	-.010	-.002	-.111
(Lag ln Demand)^2	.071	.021	.067	.576	.048	.417
(Lag ln Service Performance)^2	-.100	.039	.016	-.312	-.036	.209
(Lag ln Hiring Quantity)^2	.094	-.036	.104	-1.513	.142	.432
(Lag ln Hiring Quality)^2	-.001	.000	.000	.010	.000	.006
(Lag ln Turnover Quantity)^2	-.017	.053	-.054	.186	-.033	-1.230
(Lag ln Turnover Quality)^2	.000	.000	.001	.000	.001	.010
(Lag ln Demand)^3	.018	.014	.007	.154	.007	-.063
(Lag ln Service Performance)^3	.013	.001	-.007	-.156	-.027	-.002
(Lag ln Hiring Quantity)^3	**.127**	-.015	**.153**	-.787	**.183**	.425
(Lag ln Hiring Quality)^3	.000	.000	.000	.001	.000	.000
(Lag ln Turnover Quantity)^3	-.044	.034	-.008	.264	.011	-.802
(Lag ln Turnover Quality)^3	.000	.000	.000	.000	.000	.003
Ln Team Age	**.481**	-.060	**.813**	**2.602**	**.872**	**3.154**
Three-league System	.059	-.047	-.041	.163	-.094	-.125
League 1	**2.133**	-.881	-.330	**12.091**	-.417	**7.582**
League 2	**1.562**	-.617	-.164	**9.437**	-.234	**6.963**
League3	**.901**	-.360	-.252	**5.289**	-.226	4.052
League 4	.447	-.170	-.355	3.387	-.371	3.437
League 5	.166	.217	-.239	.586	-.180	2.183
Three Points	.145	-.012	**.120**	.167	-.025	.725
Euro Introduction	**.154**	.015	-.075	-.195	-.010	-1.089
German Reunification	**.193**	.038	-.043	**2.624**	.018	**1.921**
National Team Wins	.044	.017	-.025	.507	.001	.265
ln Population	-.101	-.172	-.678	.440	-.744	-.485

1.FC Kaiserslautern	1.420	**6.603**	**7.522**	-17.276	8.184	-6.510
1. FC Cologne	1.366	6.996	**9.020**	-18.244	9.864	-3.640
1. FC Nuremberg	1.397	6.783	**8.699**	-18.775	9.447	-4.942
1. FC Saarbruecken	.834	6.393	**8.022**	-22.112	8.616	-9.805
TSV 1860 Munich	1.172	6.886	**9.220**	-19.465	9.905	-5.338
Arminia Bielefeld	1.660	6.551	**8.499**	-2.122	9.166	-6.996
Bayer 04 Leverkusen	1.592	**6.928**	**8.034**	-15.909	**8.956**	-2.563
FC Bayern Munich	1.502	7.661	**8.907**	-16.997	9.918	-1.438
Borussia Dortmund	1.532	7.227	**8.460**	-18.147	9.389	-2.790
Borussia Monchengladbach	1.429	6.809	**8.019**	-18.562	8.818	-3.622
Eintracht Braunschweig	1.440	6.511	**7.963**	-2.288	8.590	-1.471
Eintracht Frankfurt	1.196	6.910	**8.850**	-19.182	9.643	-5.667
FC St. Pauli	2.193	6.841	**9.580**	-19.944	1.248	-5.924
FSV Mainz 05	.954	6.656	**8.818**	-2.040	9.557	-8.012
Fortuna Dusseldorf	1.242	6.595	**8.073**	-19.998	8.817	-6.259
Hamburger SV	1.336	7.163	**9.529**	-18.131	1.432	-2.554
Hannover 96	.986	6.754	**8.692**	-21.053	9.463	-6.923
FC Hansa Rostock	1.208	6.375	**7.902**	-2.740	8.571	-8.198
Hertha BSC Berlin	.963	7.200	**9.766**	-2.637	1.718	-4.709
KFC Uerdingen 05	1.272	6.619	**8.159**	-19.940	8.823	-6.874
Karlsruher SC	.704	6.304	**8.483**	-17.870	**9.150**	-6.637
MSV Duisburg	1.073	6.651	**8.543**	-21.066	9.199	-8.697
SC Freiburg	1.692	6.613	**8.302**	-18.873	**9.068**	-4.946
SV Darmstadt 98	1.315	6.929	**8.091**	-18.941	8.892	-5.375
SV Waldhof Mannheim	1.266	6.420	**7.612**	-19.055	8.340	-6.167
FC Schalke 04	1.498	6.663	**9.957**	-2.769	**1.701**	-5.162
SpVgg Greuther Fuerth	1.089	6.229	**8.051**	-21.094	8.627	-8.871
SpVgg Unterhaching	1.405	6.459	**8.807**	-2.456	**9.536**	-7.554
VfB Stuttgart	1.225	7.075	**8.636**	-17.848	9.481	-3.523
VfL Bochum	1.541	6.700	**8.571**	-19.829	9.323	-5.951
VfL Osnabrueck	1.548	6.383	**8.104**	-19.952	8.673	-8.522
VfL Wolfsburg	1.091	6.596	**7.688**	-17.591	8.333	-5.612
SV Werder Bremen	1.413	7.124	**8.460**	-18.098	9.334	-3.574
Model fit: R^2	.462	.660	.434	.476	.289	.823

Notes: Significant parameters ($p < .05$) in bold.

Table F.7: LCP, Horizon *s* = 6

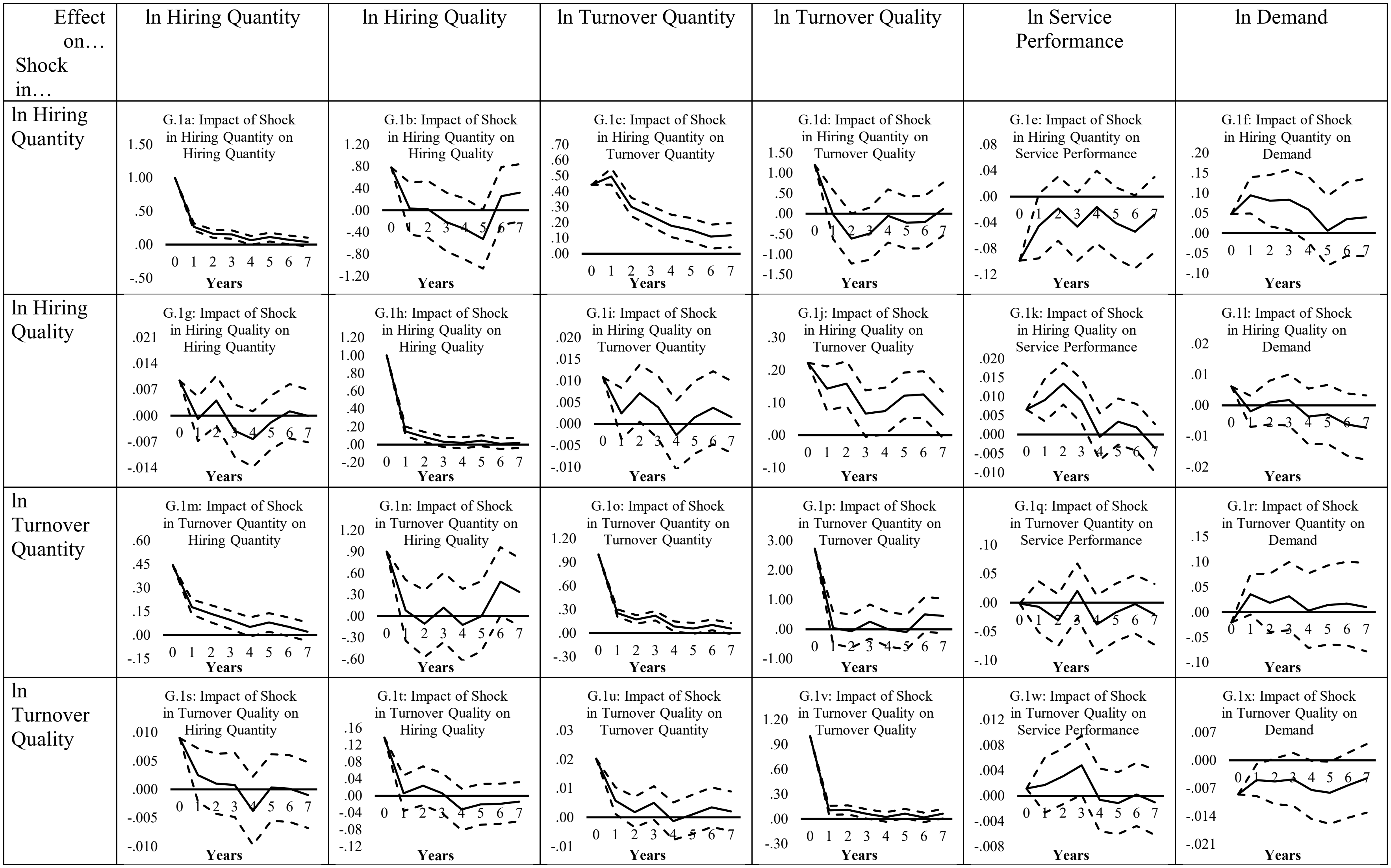
	ln Demand	ln Performance	ln Hiring Quantity	ln Hiring Quality	ln Turnover Quantity	ln Turnover Quality
Lag ln Service Performance	.034	-.019	.048	.064	.046	.741
Lag ln Demand	.073	**.075**	-.023	.444	.037	**1.160**
Lag ln Hiring Quantity	.027	-.034	.025	-.169	.017	-.191
Lag ln Hiring Quality	-.010	-.010	-.001	-.062	-.002	-.039
Lag ln Turnover Quantity	-.049	.002	-.033	.586	-.052	-.013
Lag ln Turnover Quality	.008	-.007	.005	-.037	.003	**.143**
(Lag ln Demand)^2	.082	.011	.017	.524	-.014	-.091
(Lag ln Service Performance)^2	.091	.092	-.069	-.867	.034	-1.132
(Lag ln Hiring Quantity)^2	.090	.021	.043	-.568	.074	.239
(Lag ln Hiring Quality)^2	-.001	.001	.000	.014	.000	.018
(Lag ln Turnover Quantity)^2	-.015	.037	-.012	-.441	-.020	-.786
(Lag ln Turnover Quality)^2	.000	-.001	.000	.000	.001	-.021
(Lag ln Demand)^3	.027	-.005	.008	.042	-.015	-.318
(Lag ln Service Performance)^3	.038	**.080**	-.005	-.187	.017	-.310
(Lag ln Hiring Quantity)^3	.057	.007	.033	.086	**.121**	.363
(Lag ln Hiring Quality)^3	.000	.000	.000	.002	.000	.003
(Lag ln Turnover Quantity)^3	.029	.015	.019	-.309	.029	-.152
(Lag ln Turnover Quality)^3	.000	.000	.000	.000	.000	-.003
Ln Team Age	**.528**	-.028	**.966**	**3.386**	**.974**	2.200
Three-league System	.077	-.057	-.078	.010	-.102	.247
League 1	**2.096**	-.895	-.228	**11.875**	-.329	**8.434**
League 2	**1.526**	-.616	-.061	**9.243**	-.154	**7.599**
League3	**.865**	-.370	-.167	**5.005**	-.161	4.423
League 4	.390	-.162	-.281	3.303	-.324	3.510
League 5	.142	.206	-.197	.952	-.182	2.019
Three Points	.153	-.003	.100	.081	-.033	.934
Euro Introduction	.145	.008	-.100	-.436	-.023	-.986
German Reunification	**.178**	.027	-.059	**2.414**	.022	**2.056**
National Team Wins	.022	.003	-.029	.447	.000	.297

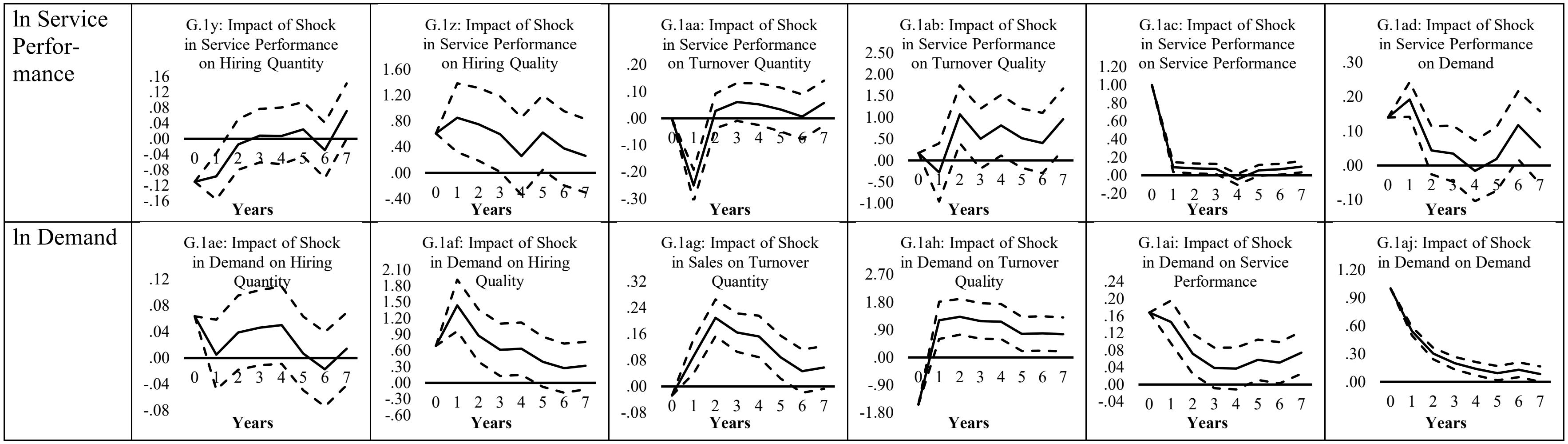
ln Population	-.164	-.046	-.361	-.260	-.502	.978
1.FC Kaiserslautern	2.006	5.057	3.316	-11.482	4.945	-2.455
1. FC Cologne	2.075	5.156	4.049	-1.657	6.081	-21.621
1. FC Nuremberg	2.058	5.018	3.950	-11.565	5.803	-21.651
1. FC Saarbruecken	1.461	4.738	3.654	-16.201	5.273	-23.863
TSV 1860 Munich	1.951	5.017	4.228	-11.844	6.110	-22.956
Arminia Bielefeld	2.323	4.852	3.970	-13.149	5.697	-22.394
Bayer 04 Leverkusen	2.202	5.356	3.701	-9.354	5.632	-18.019
FC Bayern Munich	2.244	5.802	3.850	-9.329	6.061	-2.102
Borussia Dortmund	2.209	5.465	3.660	-1.671	5.716	-19.847
Borussia Monchengladbach	2.054	5.129	3.515	-11.987	5.360	-19.760
Eintracht Braunschweig	2.104	4.808	3.506	-13.769	5.167	-25.041
Eintracht Frankfurt	1.892	5.134	4.043	-11.702	5.959	-22.522
FC St. Pauli	3.011	4.914	4.518	-12.069	6.412	-24.041
FSV Mainz 05	1.678	4.871	4.093	-12.705	5.948	-24.106
Fortuna Dusseldorf	1.896	4.947	3.753	-13.578	5.506	-21.118
Hamburger SV	2.082	5.268	4.386	-1.266	6.508	-21.195
Hannover 96	1.651	4.974	3.997	-13.914	5.859	-23.113
FC Hansa Rostock	1.808	4.821	3.566	-14.155	5.269	-22.612
Hertha BSC Berlin	1.748	5.211	4.470	-12.073	6.643	-23.590
KFC Uerdingen 05	1.934	4.943	3.637	-13.439	5.374	-21.868
Karlsruher SC	1.336	4.631	4.133	-11.477	5.828	-21.379
MSV Duisburg	1.796	4.874	3.866	-14.209	5.598	-24.625
SC Freiburg	2.362	4.984	3.936	-12.042	5.721	-2.446
SV Darmstadt 98	1.958	5.251	3.559	-12.089	5.430	-21.007
SV Waldhof Mannheim	1.867	4.846	3.407	-12.945	5.154	-2.020
FC Schalke 04	2.283	4.786	5.055	-12.368	6.979	-23.282
SpVgg Greuther Fuerth	1.712	4.627	3.769	-14.720	5.364	-23.138
SpVgg Unterhaching	2.107	4.732	4.294	-13.686	6.108	-22.759
VfB Stuttgart	1.909	5.317	3.838	-1.708	5.834	-2.564
VfL Bochum	2.209	4.978	3.962	-12.971	5.771	-21.967
VfL Osnabrueck	2.202	4.760	3.783	-13.591	5.379	-23.039
VfL Wolfsburg	1.734	4.999	3.515	-11.321	5.211	-19.527
SV Werder Bremen	2.087	5.370	3.708	-11.039	5.682	-2.359
Model fit: R^2	.444	.664	.420	.469	.331	.813

Notes: Significant parameters ($p < .05$) in bold.

WEB APPENDIX G: FULL SET OF IRF ELASTICITIES BASED ON LOCAL PROJECTIONS

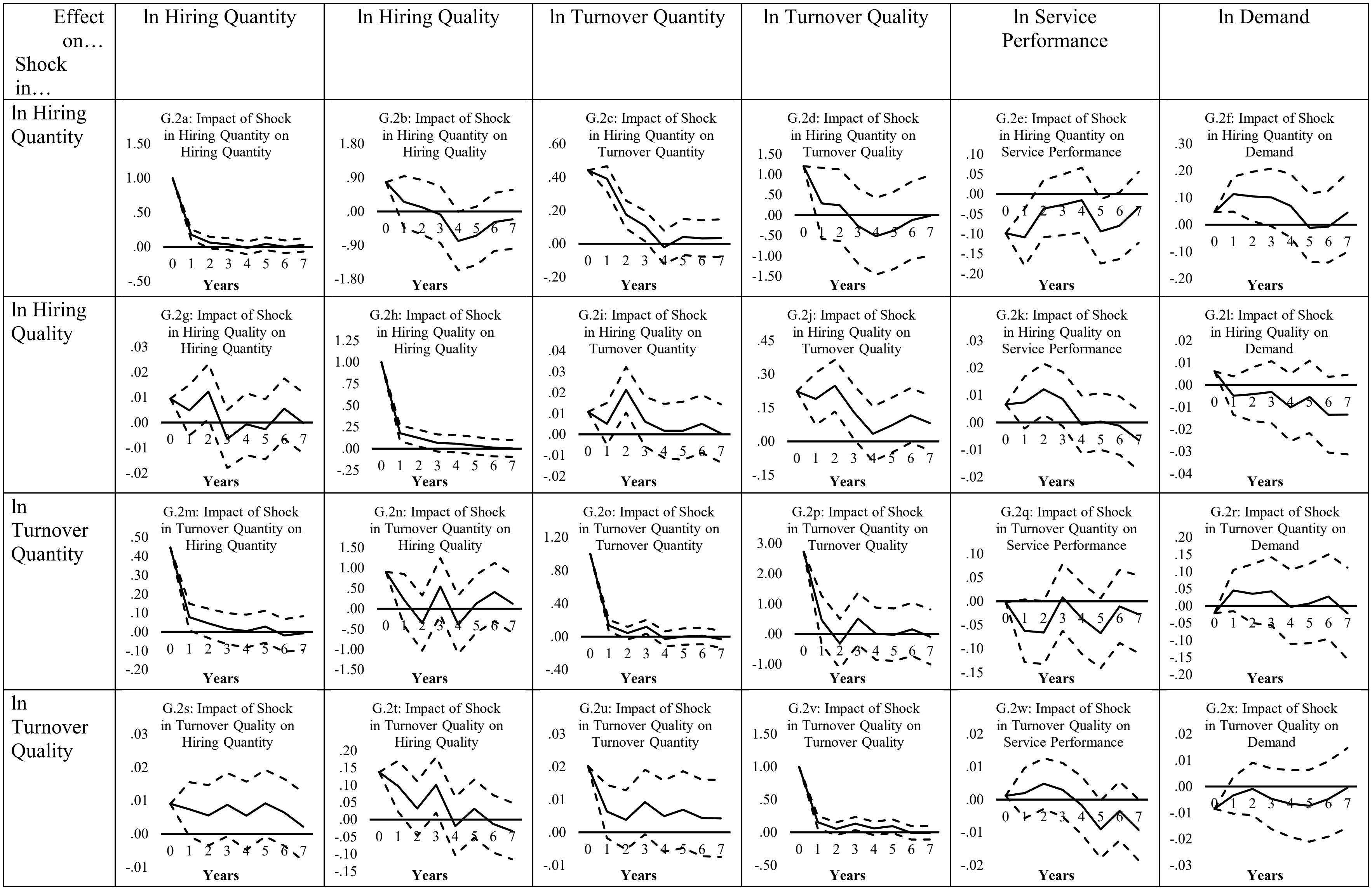
Figure G.1: IRF Elasticities Based on LLP

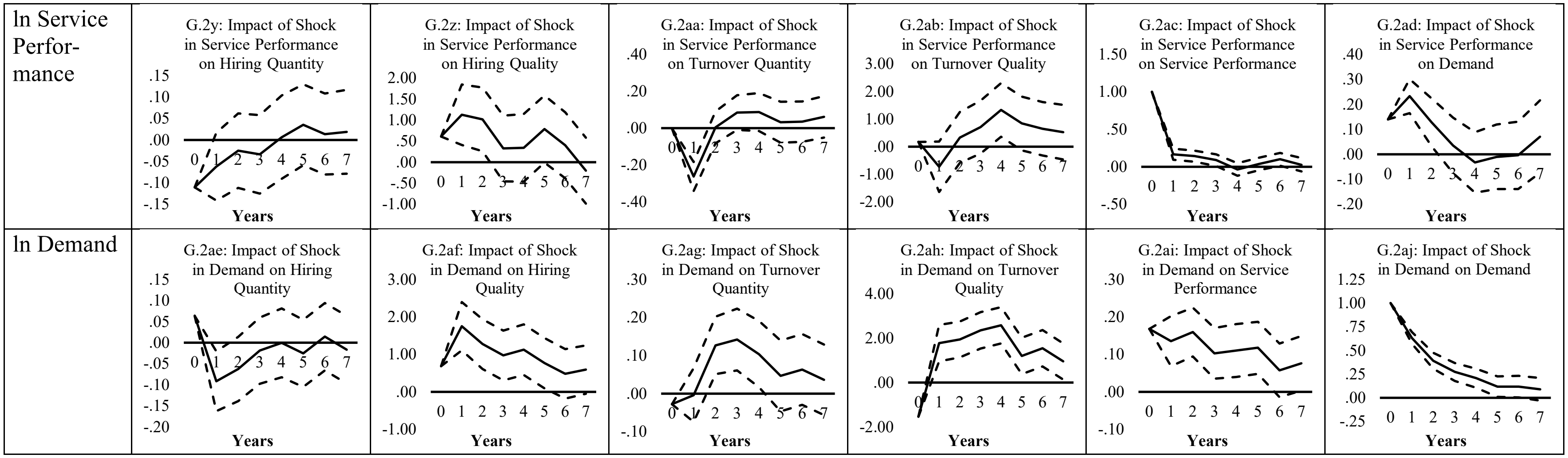




Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

Figure G.2: IRF Elasticities Based on LCP





Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

WEB APPENDIX H: HOLDOUT VALIDATION

We conduct a holdout validation to test model performance for data that were not used for model estimation. Using the last 10% of observations for each club as holdout and standardizing the endogenous variables per club for comparison, we reestimated the models and calculated different holdout performance measures for VAR-X, LLP and LCP. For the VAR-X model period t is predicted based on the predictions of period t-1 to t-p. If T is the last period used for estimation, and, e.g., T+3 is to be predicted, then the VAR model proceeds in three steps by first predicting T+1 based on the observations in T-p+1 to T, then T+2 based on the prediction of T+1 and the observations of T-p+2 to T and finally T+3 based on the prediction of T+2 and T+1 the observations of T-p+3 to T.

We adapt the local projections approach, which is primarily designed for obtaining IRFs, for holdout prediction. Local projections use the direct predictions as based on the different horizons' regressions. Thus, to predict for period T+1 (outside the estimation sample), we use the estimates from the estimation sample (up to time T) with s=0; for time T+2 we use s=1 and observations up to time T; for time T+3 we use s=2 and observations up to time T.

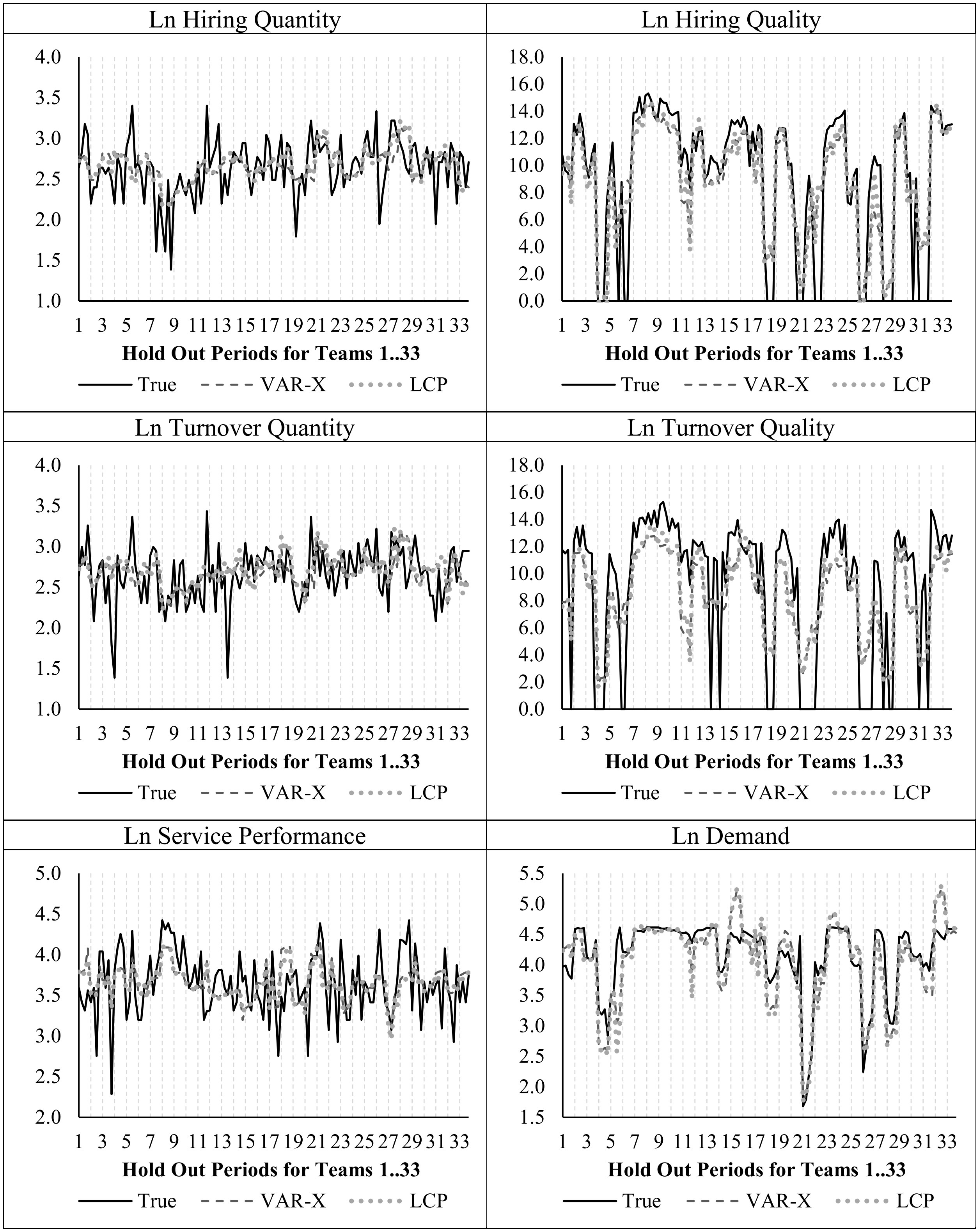
The performance measures are provided in Table H.1 and the graphical comparison for the non-standardized data is depicted in Figure H.1.

Table H.1: Holdout Fit for Last Four Years

Measure	Mathematical Expression	VAR-X	LLP	LCP
Overall Correlation	$\mathrm{Corr}(y_{itk}, \hat{y}_{itk})$ for team i, year t, variable k	.9837	.9829	**.9838**
Average Pooled Corr. across Teams	$\frac{1}{J}\sum_{j=1}^{J} \mathrm{Corr}(y_{jtk}, \hat{y}_{jtk})$	.8669	.8598	**.8649**
Mean Squared Error (MSE)	$\frac{1}{TJn}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{n}(y_{jtk} - \hat{y}_{jtk})^2$	.5655	.5901	**.5628**
Mean Absolute Error (MAE)	$\frac{1}{TJn}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{n}\lvert y_{jt} - \hat{y}_{jt}\rvert$	.5655	.5733	**.5597**
Mean Absolute Percentage (MAPE)	$\frac{1}{TJn}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{n}\frac{\lvert y_{jt} - \hat{y}_{jt}\rvert}{y_{jt}} \times 100\%$	11.1771	11.2797	**11.0963**
Theil's U	$\sqrt{\frac{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{n}(y_{jtk} - \hat{y}_{jtk})^2}{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{n}(y_{jtk} - y_{jt-1k})^2}}$	.6969	.7272	**.6936**

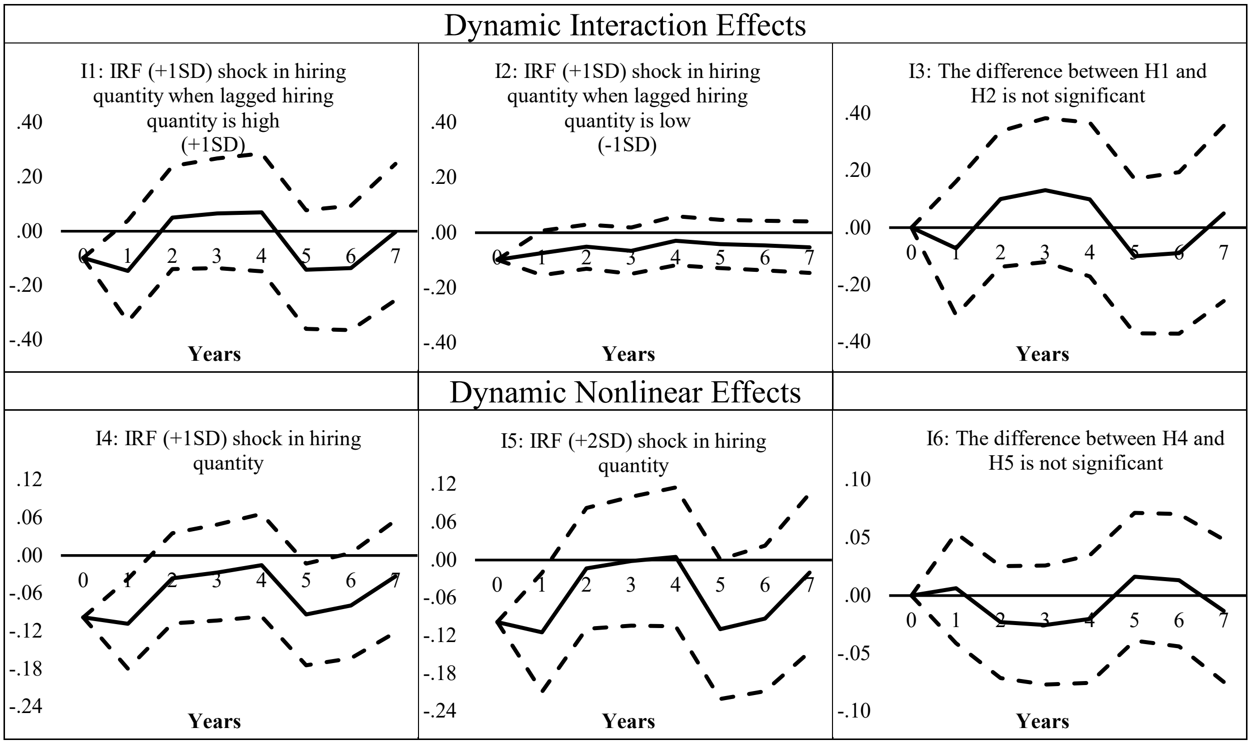
Notes: The bold, underlined figures represent the best holdout sample fit based on standardized data.

Figure H.1: Depiction of Holdout Fit



Notes: Graphs show lined up 4 hold-out periods for each of the 33 teams in the data sample.

WEB APPENDIX I: IRF ELASTICITIES SHOWING THE FLEXIBLE DYNAMIC EFFECTS OF HIRING QUANTITY ON SERVICE PERFORMANCE BASED ON LCP



Notes: — mean, --- 95% CI. The y-axis reports arc elasticities.

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