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Source-Dependent Preferences: Theory and Applications

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Abstract

This dissertation examines behaviour that violates the assumption of fungibility. The first chapter presents a psychologically founded explanation for these violations, generalises consumer theory to accommodate such behaviour, and relates the results to empirical evidence. It also demonstrates that policy can use this behaviour to increase welfare. The second chapter comprises two studies that provide additional evidence regarding violations of fungibility on the labour market and in co-operative behaviour.

Zusammenfassung

In dieser Dissertation untersuche ich mit theoretischen und empirischen Methoden Verletzungen der Fungibilitätsannahme. Im ersten Kapitel schlage ich eine psychologisch fundierte Erklärung für solche Verletzungen vor. Um entsprechendes Verhalten theoretisch analysieren zu können, erweitere ich klassische Konsumententheorie und setze die Ergebnisse anschließend in Bezug zu empirischer Evidenz. Zudem zeige ich, dass politische Entscheidungsträger dieses Verhalten wohlfahrtssteigernd nutzen können. Das zweite Kapitel umfasst zwei Studien, in denen ich zusätzliche Erkenntnisse über Verletzungen der Fungibilität auf dem Arbeitsmarkt und im kooperativen Verhalten erarbeite.

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To my father

Contents

Introduction and Contribution

Since the economic crisis had gone off in 2007, the science of economics has faced increased and sustained criticism. One popular case against it questioned economists' unrealistic assumptions about human behaviour. As Krugman (2009) argued, the idea of a rationally and selfishly behaving homo economicus had hindered economists to predict developments on the financial markets that have ultimately culminated in economic turmoil, the aftermath of which we still experience today.

Some criticism may be justified. However, the allegations that economists generally disregard behaviour that is at odds with the neoclassical description of the homo economicus are short-sighted. During the past decades, the field referred to as behavioural economics has suggested various departures from the neoclassical model. The constant ambition in doing so has always been to make economic analysis and its assumptions more realistic (Camerer and Loewenstein, 2004). In line with corresponding empirical evidence from inside and outside the laboratory, economists have incorporated other-regarding preferences, such as reciprocity (Rabin, 1993; Falk and Fischbacher, 2006) and inequity aversion (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000), non-linear probability weighting (Quiggin, 1993), and hyperbolic discounting (Laibson, 1997), among others, into economic analysis. These approaches have helped to improve the predictive power of economic models and have led to diverse new policy implications (Chetty, 2015).

Most of these models modify or relax assumptions made in the neoclassical model (e.g. selfishness, linear probability weighting, and exponential discounting) to allow for more realistic behaviour. However, one assumption has received little attention. In contrast to the permanent income hypothesis (Friedman, 1957), it is unlikely that people take into account their entire currently available budget in equal measure when it consists of more than one income source, or their life-time income when it is received at different points in time. In other words, the assumption that people treat money as a fungible resource is disputable. According to Camerer and Loewenstein (2004), and Hastings and Shapiro (2013), violations of fungibility have implications for several policies, such as the promotion of savings (Thaler, 1994), income tax withholding (Feldman, 2010), tax-deferred retirement accounts (Thaler, 1990), and fiscal stimuli (Sahm et al., 2012).

This dissertation aims at contributing to three distinct strands of literature that explore violations of fungibility, its origins and consequences. Chapter I investigates consumer choice under the assumption that an agent's decisions may vary with the composition of her total income, and derives implications for public policy. With a broader interpretation of fungibility of resources, Section II.1 studies whether hiring costs of professional football players affect the playing time allocated to them by their manager. Section II.2 experimentally tests the relation of income source, cognitive abilities, and co-operative behaviour.

I approach violations of fungibility from a theoretical perspective in Chapter I.[1] A non-negligible amount of research demonstrates that human behaviour often violates the assumption of fungibility: in spending child benefits (Kooreman, 2000; Blow et al., 2012), governmental stimulus transfers (Buddelmeyer and Peyton, 2014), bequests (Zagorsky, 2013), and lottery gains (Briggs et al., 2015), and in lab and field experiments (Cherry, 2001). However, despite the evidence and its implications for public policies and private organisations, there is little research on how to formalise models of consumer choice that allow for violations of fungibility and on how to explain these (I will discuss exceptions in Section I.2.1).

Both issues are addressed in Chapter I where I discuss how the source of income might affect decision making. First, I generalise consumer choice theory by allowing agents to exhibit different preferences for different income sources. I call this type of preferences *source-dependent preferences*. Although Loewenstein and Issacharoff (1994) suspect that allowing violations of fungibility might make it difficult to model consumer behaviour, I demonstrate as a first result that consumer theory is still feasible if the assumption

[1]This chapter was circulated under the title "A Model of Source-Dependent Preferences".

of fungibility is relaxed. This affects some results of classical consumer theory. With source-dependent preferences, consumer response may depend on whether an increase of total income is due to all income sources increasing simultaneously or due to the increase of only one income source. Therefore, homogeneity applies only on condition that all income sources increase at the same rate. Furthermore, allowing income sources to affect consumer choice and utility restricts the interpretation of a numeraire good to the level of consumption of all goods other than that under consideration, and rules out its simple interpretation as "money" (e.g. Brekke, 1997). By contrast, other properties such as those of the Cournot and Engel aggregation are not affected.

The presented model predicts one element of behaviour which Thaler (1985, 1990, 1999) terms mental accounting. He describes that individuals use a system of mental accounts to categorise and evaluate expenditures and income sources. Mental accounting constitutes an informal concept that can accommodate why we might observe that some economic agents exhibit distinct preferences for different sources of income. However, it is only a meta-theory that does not provide predictions about which income is spent how (Epley et al., 2006, p. 215).

To make predictions about the directions of violations of fungibility, I make use of insights from psychological research. More specifically, psychological ownership (Pierce et al., 2001, 2003) describes ownership not as a binary state but as a continuum. According to the theory, feelings of ownership emerge once one controls or invests into an object. This suggests that the more one has invested (e.g. effort or money) into a certain outcome, the more one feels entitled to it. Consequently, due to this entitlement, income that has been generated by own investments is also more likely to be used for expenditures serving one's own needs. As I will elaborate on in Section I.2.2, this behaviour seems to have evolutionary roots and to fulfil genetic as well as social motives.

The theoretical foundation introduced in Chapter I can accommodate these insights. The resulting model can predict behaviour as observed in experiments and field studies. Calibrations with estimates from a broad range of empirical papers give an impression of the extent of source-dependent preferences. They also indicate that smaller transfers are more effective than larger ones in prompting subjects to consume a targeted good.

Finally, I illustrate how an approach that allows for source-dependent preferences can alter results and implications from models assuming the fungibility of money. In the context of consumption externalities, I characterise how redistribution through labelled transfers can improve welfare. In contrast to the result generated by assumptions that are common in classical optimal taxation (Sheshinski, 1972), I show that a utilitarian social planner can improve welfare by exploiting an agent's tendency to treat income sources differently. Due to the weaker sensation of psychological ownership attributed to a transfer, agents may be more easily convinced how to spend the transfer (e.g. by the use of a label). Thereby, redistribution can increase consumption of a targeted good and alleviate the inefficiency caused by a positive externality.

In the first section of Chapter II, I investigate violations of fungibility in the field.[2] Money is not the only resource that is used to fulfil goals and needs. In a business context, next to capital, labour is used to produce and to generate profits. Under the assumption that two workers are equally productive, they can be considered perfect substitutes, thus fungible. In some industries, labour incurs up-front costs in addition to running expenses. Once incurred, the former often constitute sunk costs. They are thus comparable to effort exerted to earn income, which is sunk at the time of the receipt of income and consumption decisions. According to neoclassical economics, sunk costs, be it effort or recruitment costs, should be ignored in the decision-making process. However, experimental evidence tells us that subjects often fail to do so (Friedman et al., 2007). Similarly, the way in which personnel has been hired might matter for managerial decision making.

Besides a number of experimental studies that establish a sunk-cost effect, evidence using (corporate) field data remains scarce (Keefer, 2017). Most empirical articles use data from draft systems in professional sports and analyse whether a player's draft order affects his time on the pitch. In contrast to the draft system, in European football teams frequently spend large amounts of money on transfer fees. The discrepancy between fee-bound and free transfers raises suspicion that one might encounter the sunk-cost fallacy among football managers.

[2]This chapter is based on the article "Ignoring Millions of Euros: Transfer Fees and Sunk Costs in Professional Football", forthcoming in the *Journal of Economic Psychology*. Please see https://doi.org/10.1016/j.joep.2018.10.006.

Using data from Germany, I investigate whether this is indeed the case, i.e. that player utilisation is affected by initially paid transfer fees. I hereby contribute to the literature in three ways. To the best of my knowledge, I am the first to examine the sunk-cost fallacy in European sports and professional football. Second, I am able to control for confounding factors previous studies have expressed concern about, the popularity of players and whether players were acquired during the coach's own spell. Third, I conduct the analysis on the level of individual matches, thereby obtaining a sample size many times larger than those of comparable studies.

As the main empirical strategy, I use a two-stage Tobit estimation to regress a player's time on the pitch on the transfer fees his current team has incurred. In the first stage, I precede the Tobit estimation with a linear regression predicting the player's current performance using lagged performances. Unlike the majority of previous articles that studied the sunk-cost fallacy in the context of professional sports (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995), I am unable to find evidence supporting this behavioural bias on a seasonal level. A more detailed analysis on the match level reveals a sunk-cost effect which, however, is economically negligible and decreases with a player's tenure. The results therefore corroborate a rational behaviour among professional sports team managers.

This is in contrast to the findings from the aforementioned experiments (e.g. Cherry, 2001) and questions the relevance of psychological ownership, which is used to predict violations of fungibility in Chapter I. However, there are two accounts that could explain why I do not find an economically significant effect of the investment to acquire a player on his playing time. First, Palacios-Huerta and Volij (2008) show that professional experience in a given context can promote rational behaviour. Second, professional football managers are more reliant to act rationally than students, who are usually the subjects in experiments (Exadaktylos et al., 2013). In a day-to-day context, people usually do not experience negative feedback once they violate fungibility. Without the incentive to abstract from the source of income, people might be more likely to give in to their predispositions. By contrast, professionals who are quickly penalised for irrational decisions might be more likely to overrule these predispositions. Similarly, Falk and Szech (2013) experimentally document how market interaction can erode moral values. None of the experimental designs uncovering violations of fungibility embeds market interaction. My results suggest that market interaction could also alleviate behavioural biases such as the sunk-cost fallacy.

In the second section of Chapter II, I report a paper-and-pencil experiment, in which I test to what extent violations of fungibility are correlated with a decision maker's cognitive ability.[3] More precisely, I investigate the relation of endowment origin, cognitive abilities, as measured by the Cognitive Reflection Test (CRT; Frederick, 2005), and co-operation in a one-shot linear public goods game. At the beginning of the experiment, the subjects are randomly divided into three treatment groups. All groups have to complete a real-effort task to earn their experimental endowment. However, all subjects receive the same endowment but have to complete different fractions of the same task (10, 50, and 90 percent). Correspondingly, the subjects receive 90, 50, and 10 percent, respectively, of their endowment for free. Subsequently, subjects decide on which proportion of their endowment to invest in a one-shot three-person linear public goods game. Finally, subjects perform the CRT and complete a questionnaire on demographic information.

The results show that subjects' contributions depend on an interplay of cognitive abilities and endowment origin. While a house money effect exists for subjects with low CRT scores, there is no such effect for those with high scores: The former contribute more when their income has been allocated to them and less when their income has been obtained by effort. By contrast, the latter contribute the same amount independent of the source of income.

The findings may have several implications. Clearly, the results demonstrate that for the design and interpretation of past and future experiments, researchers should carefully reflect whether subjects are given or have to earn their endowment, particularly when including measures of cognitive ability. Furthermore, public goods games have a redistributive character and involve a free-rider problem. Empirical studies of taxation and tax compliance should bear in mind that the source of income can affect preferences (c.f.

[3]This chapter was circulated under the title "Not All Income is the Same for Everyone: Cognitive Ability and the House Money Effect in Public Goods Games".

Bühren and Kundt, 2014). Finally, as team production can also be compared to a public goods game (Alchian and Demsetz, 1972), how agents receive production inputs (e.g. information) could alter team member's propensity to co-operate.

Reviewing the results from both studies in Chapter II suggests that source-dependent preferences as introduced in Chapter I seem to be most prevalent among inexperienced individuals and those with limited cognitive capacities. Consequently, policies that impact the composition of income or exploit source-dependent preferences (as in the application in Section I.5) might affect these subgroups differently. Policy makers should take this into consideration when designing policy measures.

Chapter I.

A Model of Source-Dependent Preferences

I.1. Introduction

Since Thaler and Sunstein (2008) it is becoming increasingly popular to use psychological insights about human behaviour to "nudge" people towards better decisions. So far, most of the interventions (e.g. default options, Madrian and Shea, 2001) have relied on psychological observations such as status quo bias, and effects of anchoring or framing. By contrast, one behavioural pattern has received little attention. Imagine you are asked to donate for a good cause just after (i) you were awarded 100 Euros in a best-paper contest or (ii) you found 100 Euros on the street. Would you behave differently? Empirical evidence suggests that many people do (e.g. Cherry, 2001).

However, most economic research builds on the assumption that money is fungible such that choices are independent of the source of income and the composition of total income. This is why Loewenstein and Issacharoff (1994, p. 166) argue that existing models cannot explain economic anomalies like the reluctance of poor working people to go on welfare when benefits are cut one to one for each dollar earned. Moreover, the assumption of fungibility is critical due to the potential impact of its violations on the effect and effectiveness of public policies (Hastings and Shapiro, 2013, p. 1450). As taxation and redistribution affect income composition, these policy measures might alter economic behaviour and affect people's well-being in addition to the more commonly known distortions (e.g. of labour supply decisions).[1] Hastings and Shapiro (2013, p. 1450) point out that there is little research on how to formulate models that do not rely on the fungibility of money.[2] However, a holistic theoretical foundation incorporating corresponding effects is necessary to derive social welfare judgements and appropriate policy applications.

This chapter contributes to recent attempts to fill this gap by relaxing the assumption of fungibility and incorporating source-dependent preferences[3] into consumer choice theory. For this purpose, I build on psychological ownership theory (Pierce et al., 2001, 2003) which describes ownership not as a binary state but as a continuum. Importantly, psychological ownership does not have to coincide with legal ownership. In fact, psychological ownership theory suggests that the more someone has invested (e.g. effort or money) into a certain outcome the more she feels entitled to it. Consequently, due to this perception of entitlement, income that has been generated by one's own investments is also more likely to be used for expenditures serving one's own needs. As a result, a model based on psychological ownership predicts violations of fungibility and behaviour also known as mental accounting.

I proceed as follows. In Section I.2, I review the literature on mental accounting and how its occurrence is explained by existent studies. Then, I introduce the concept of psychological ownership in more detail, discuss evolutionary origins, and draw conclusions for how it might affect preferences. Based on that concept, I present a formalised theory of source-dependent preferences in Section I.3. To the best of my knowledge, I am the first to explain violations of fungibility and the occurrence of mental accounting with the help of psychological ownership. In line with the conclusions drawn from the corresponding psychological research, I argue that violations of fungibility are the result of a deliberate decision-making process. I specify a class of source-dependent utility functions to explain empirical findings in Section I.4. With the help of a concrete application, I exemplify the

[1] For examples consider income tax withholding, Feldman, 2010; tax-deferred retirement accounts, Thaler, 1990; and fiscal stimuli, Sahm et al., 2012.

[2] The papers closest to this chapter are Farhi and Gabaix (2015), who explain violations of fungibility with misperceived budget constraints, and Koszegi and Matějka (2018), who obtain these violations as a result of limited attention.

[3] This term follows Loewenstein and Issacharoff (1994) who discuss source dependence in the valuation of objects.

implications of source-dependent preferences for public policy in Section I.5. Psychological ownership suggests that individuals maximise their utility when exhibiting source-dependent preferences. Therefore, policy makers should not aim to correct this behaviour. However, source-dependent preferences offer a path to mitigate market failures. When compared to bans, in-kind transfers, or earmarked vouchers, source-dependent preferences allow for non-intrusive ways to steer choice towards the internalisation of externalities. To demonstrate this, I use a specification of source-dependent preferences to examine welfare effects of redistribution through labelled transfers in the context of positive externalities. I conclude in Section I.6.

I.2. Literature

I.2.1. Mental accounting

Thaler (1985, 1990, 1999) argues that individuals use certain rules to organise their funds and expenditures. This set of rules is referred to as mental accounting.[4] One important component is to label funds and income streams, to group purchases into categories, and to link these funds to specific categories of goods, which leads to violations of fungibility. These violations have been identified by empirical economists (e.g Baker et al., 2007; Hastings and Shapiro, 2013). By contrast, there is a lack of formal theoretical analyses that attempt to explain violations of fungibility and that could be used to investigate implications for businesses and public policy. The concept of mental accounting does not offer formal predictions about the composition of accounts and how they might be spent (Epley et al., 2006, p. 215).

Farhi and Gabaix (2015) provide a theoretical framework that can encompass mental accounting. Their approach differs from the one in this chapter in two aspects. Particularly, the authors arrive at a violation of fungibility by assuming that agents optimise their consumption decision subject to a perceived budget constraint that differs from the real one.[5] This seems plausible with more complex decisions. However, subjects violate

[4] Zhang and Sussman (2018) provides a recent review on mental accounting.

[5] In the approach by Farhi and Gabaix (2015), an individual maximises her utility subject to a *perceived* budget constraint $c_1+c_2+\kappa_1|c_1-\omega_1^d| = w^*+t+b$ instead of the actual budget constraint $c_1+c_2 = w^*+t+b$.

fungibility in very simple experiments. Even if income is not labelled or earmarked, vouchers are non-distortive, and budget constraints are almost impossible to misperceive, there is evidence that income sources affect consumption choices (Cherry, 2001; Cherry et al., 2002; Carlsson et al., 2013; Abeler and Marklein, 2017). This cannot be explained by the model introduced by Farhi and Gabaix (2015). With constant prices and budgets, income composition might in fact influence preferences as suggested by psychological ownership. Second, Farhi and Gabaix (2015) consider only earmarked income, particularly, vouchers that can only be spent on a certain good. Yet violations of fungibility also occur with non-earmarked income (Cherry, 2001; Cherry et al., 2002; Carlsson et al., 2013).[6]

Koszegi and Matějka (2018) view mental accounting as the result of an agent optimally allocating her limited attention in consumption decisions. The authors argue that with substitutes the agent may find it optimal to only consider which of the substitutable goods to consume, and not to think about the consequence for remaining funds and the consumption possibilities for other goods. By contrast, with complements, the agent may consider it more important to think about how much to consume in total rather than their relative consumption levels. As a result, the consumer appears to spend as if she was constrained by budgets which are formed according to the substitutability of goods. The authors also provide an explanation for a higher marginal propensity to consume with shocks to the checking account compared to shocks to the investment account. Due to the higher interest rates on overdraft, the agent pays closer attention to the former. She is thus also more likely to notice and respond to shocks to the checking account.

On the right-hand side, w^* is pre-tax income, t is a general transfer, and b is a voucher that can only be spent on good c_1. On the left-hand side, c_1 and c_2 are the goods, ω_1^d is a default level of consumption of c_1, and κ_1 is the degree to which deviating from the default harms the consumer. Farhi and Gabaix (2015) describe κ_1 also as degree of mental accounting. The default is set by the consumer by $\omega_1^d = \alpha_1 w + \beta b$. Note that Farhi and Gabaix (2015) distinguish between decision and experienced utility. Since I only want to demonstrate how they model mental accounting, I ignore that for simplicity and only denote α_1 instead of α_1^s. Further, β constitutes the degree of mental accounting. α is the marginal propensity to consume c_1 out of w^* or t. If κ_1 is sufficiently large, that is the consumer suffers a lot from not conforming to the default, she will consume $c_1 = \omega_1^d = \alpha_1(w^* + t + b) + \beta b$. Hence, when receiving a voucher b, an individual that exercises mental accounting at least to some extent will increase the default level ω_1^d and consumption of c_1 even if the voucher is actually non-distortive, $c_1 > b$ (c.f. Abeler and Marklein, 2017).

[6] Yet one could easily extend their model to provide analogous results with labelled income or income that is only associated with the consumption of certain goods. Similarly to a perceived budget constraint, agents could be assumed to consider labelled transfers or other income to be earmarked for certain goods by mistake.

Koszegi and Matějka (2018) present an explanation for the grouping of goods, one aspect of mental accounting. By contrast, they cannot explain the link between specific income sources and goods (Abeler and Marklein, 2017; Hastings and Shapiro, 2018), although limited attention might also matter in this regard. Furthermore, they only distinguish between income shocks to the checking and to the investment account. However, income shocks to the checking account can occur in various forms. For example, non-labour income such as transfers is particularly important to lower-income households who also seem to be more likely to exhibit mental accounting (Antonides et al., 2011). This aspect is covered in this chapter.

Based on psychological ownership, I argue that past non-monetary investments affect consumer choice. Similarly, individuals tend to honour sunk costs (Arkes and Blumer, 1985). As this tendency is also observed if the sunk cost is effort (Cunha and Caldieraro, 2009), there might be a link between violations of fungibility and sunk-cost effects.

While most studies on sunk-cost effects are purely empirical, Ho et al. (2018) additionally formulate a consumer choice problem that incorporates sunk costs. They investigate how sunk costs that occur with the purchase of a car in Singapore (the ex-policy price, a registration fee, and the price for a certificate of entitlement[7]) affect car usage. Their model predicts that sunk costs induce higher-than-rational[8] usage in the first months. They can confirm this prediction using administrative data. Put differently, a driver who owns two otherwise identical cars that only differ in their level of sunk costs does not use them evenly as predicted by classical economic theory. Instead, the car with the larger sunk costs is used excessively. Thus, how one has obtained the cars (with more or less sunk costs) matters for decision making.

Ho et al. (2018) assume that sunk costs directly affect a consumer's utility. Although the authors do not discuss whether honouring sunk costs increases or decreases utility, they conclude that the increased usage induced by sunk costs is higher-than-rational. Hence, they reason that an increase in sunk costs decreases utility for individuals who

[7]The registration fee and the price to acquire a certificate of entitlement are two measures to limit the car population in the small, densely populated city-state.

[8]The authors conclude that usage of cars with high sunk costs is higher than rational consumers would choose.

respect these sunk costs. However, it is conceivable that, in reality, people are better off respecting sunk costs rather than mimicking rational behaviour by ignoring them.[9]

I.2.2. Psychological ownership

Theoretical foundations

Classical economic theory assumes that "all monies are the same" (Zelizer, 1989, p. 347). However, there are attributes that distinguish one income from another. While earnings imply that an individual has exerted effort to obtain the income, other funds come surprisingly or without prior effort: windfall income, bonus payments, and dividends. Furthermore, there are income sources that come with a label (e.g. from the government as with child benefits, or an implicit one as with unethically earned money).

Economists usually assume that individuals sum up all their incomes, take the total amount, and allocate it according to their preferences. In doing so, information that people appear to take into account when making decisions is omitted. Hence, model extensions that include these attributes are sensible.

One dimension along which income sources vary are associated costs. Costs required to receive income can affect the extent to which people feel that they deserve the income's ownership. Research from psychology suggests that ownership is not necessarily only a matter of legal property, but a more complex psychological phenomenon. It characterises ownership as a continuous rather than binary state. According to Pierce et al. (2001, 2003) psychological ownership over objects can emerge through three routes. Two of them are of major importance in this context and are also speculated to be most effective in generating psychological ownership (Pierce et al., 2003, p. 96). First, having control over an object promotes feelings of ownership. Already Jeremy Bentham (1843) recognises that the expectation of how to use an object is part of the concept of property:

> "Property is only a foundation of expectation – the expectation of deriving certain advantages from the thing said to be possessed, in consequence of the

[9] Under this assumption, increasing sunk costs could even increase utility for individuals who tend to respect sunk costs.

relations in which one already stands to it" (Bentham, 1843, Part I, Chapter XIII).

For that expectation to be justified, objects must be or become under control. Second, the investment of time, ideas, skills, and physical, psychological, and intellectual energy into an object or into obtaining an object develop psychological ownership over the object (Pierce et al., 2001, p. 302). The idea that the sense of property is a result of preceding effort has already been posited by John Locke (1689). This seems to be particularly crucial when considering income.[10] Varying on these dimensions, it is possible that income sources might differ in their degrees of psychological ownership and might thus also be valued and allocated differently.

Pierce et al. (2001, 2003) also discuss potential roots of psychological ownership. Generally, they conclude that it satisfies both genetic and social motives (Pierce et al., 2001, p. 300).[11] More precisely, possessions allow individuals to experience efficacy and effectance. In psychology, these terms refer to the feeling of having a causal impact in an environment. Moreover, people use possessions to build their self-identity.

Observations by ethologists, psychologists, and behavioural scientists support the view that valuations depend on the way objects have been obtained. They also emphasise a genetic origin. Numerous studies find that animals work for food in the presence of free food, and under certain conditions even prefer to work.[12] This behaviour, called contrafreeloading, is found across species,[13] thereby suggesting a fundamental pattern in organisms. In line with the rationale of Pierce et al. (2001, 2003) some of the studies explain this observation with a need to experience competence, the motivation to control and modify the environment (White, 1959). In addition to that, reviewing several decades of empirical research, Magalhães and White (2016) conclude that humans as well as non-

[10] Third, Pierce et al. (2001, 2003) argue that detailed knowledge about an object can foster feelings of ownership.

[11] Psychological ownership can be compared to pro-social behaviour, whose roots also appear to be genetic and social (Wallace et al., 2007; Cesarini et al., 2008; Reuter et al., 2011).

[12] See Osborne (1977) for a review.

[13] Contrafreeloading is found in mammals, including rats (Jensen, 1963) and humans (Singh, 1970; Singh and Query, 1971; Tarte, 1981), fish (Baenninger and Mattleman, 1973), birds (Neuringer, 1969), and even invertebrates (ants, Czaczkes et al., 2018).

humans exhibit sunk-cost effects. Hence, there is cross-species evidence that subjects (ex ante) have a preference for earning objects, and (ex post) value invested effort.

Correspondingly, Ellis (1985, p. 122) argues in favour of an evolutionary cause. In his view, the urge to control is beneficial for influencing the distribution of resources to one's own advantage. Consequently, organisms might have evolved in a way to support such behaviour, e.g. in strengthening preferences for earned objects. Further, Sweis et al. (2018) hypothesise that invested effort might be as predictive for future valuations as forecasting these valuations themselves but cognitively easier to retrieve. Based on this assumption, the authors speculate that animals may have evolved processes that base their estimates of future valuations on invested effort. Two further evolutionary reasons that might have favoured a preference for earned objects and earning objects come to mind. Experience might teach animals not to trust free food. Left behind prey or windfall might already be rotten and inedible. Animals who take the effort to hunt for themselves or climb a tree to get food therefore might have an evolutionary advantage. This might have led to an innate inclination to provide effort to obtain food/goods rather than to go with free choices. Finally, having worked for obtaining an object can be observed by others and can therefore serve as a signal to be willing to defend it. Thus, animals might have an incentive to work for their food if this discourages theft. From an evolutionary perspective, a preference for earned food might have been advantageous and might have prevailed. With these preferences genetically predisposed, choices that are associated with one's own effort would feel more attractive.

Psychological ownership and the endowment effect

Psychologists assign important behavioural consequences to psychological ownership (Pierce et al., 2001, 2003). It has emerged as one of the main theories, next to prospect theory, to explain the endowment effect (Reb and Connolly, 2007; Morewedge et al., 2009; Ericson and Fuster, 2014). The endowment effect demonstrates how a sense of ownership influences preferences and behaviour.

Using a tailored design,[14] Reb and Connolly (2007) replicate the endowment effect. Participants who owned and possessed the object valued it more than those who neither owned nor possessed it. More importantly, the authors demonstrate that only physical possession but not legal ownership as conveyed by the experimenter is responsible for the endowment effect to emerge. The valuation of the objects only increased upon receipt of possession but not of legal ownership. This difference in valuations appeared to be mediated by feelings of ownership, supporting psychological ownership theory.

Morewedge et al. (2009) take a different approach and demonstrate that ownership status instead of loss aversion accounts for the endowment effect.[15] They also replicate the endowment effect between participants who own and can sell the object (owner-sellers) and participants who do not own and can buy the object (non-owner-buyers). In addition, they find that valuations by participants who already own the object and are asked to state their willingness to pay for another unit (owner-buyers) are not significantly different from those of owner-sellers but significantly larger than those of non-owner-buyers. This finding

[14] In two 2 (Ownership vs. No Ownership) x 2 (Possession vs. No Possession) between-subjects design experiments, Reb and Connolly (2007) compare participants' choices (and additionally participants' willingness to accept and willingness to pay in experiment two) between a chocolate bar (first experiment) or a coffee mug from the participants' university (second experiment), and varying amounts of money. By design, a quarter of the participants possessed and were told that they owned the object and had the choice to sell it. The second group did not possess but was told that they owned the object and had the choice to sell it. By contrast, the third and fourth group were told that they did not own the object but had the choice to buy it. While group three already had the object in possession, group four did not.

[15] In a valuation paradigm, they examine the willingness to accept (selling) prices and the willingness to pay (buying) prices by the following four groups. The first group are sellers who own the object (a coffee mug in their case). As they are asked their selling price, they are referred to as owner-sellers. Non-owner-buyers are participants who do not own the object and are asked their willingness to pay to get it. These two groups are the standard conditions that are usually compared to detect the endowment effect. In addition, Morewedge et al. (2009) study the willingness to pay to get another identical mug by participants who already own one (owner-buyers). This condition was used to identify loss aversion or ownership as the main driver of the endowment effect. Loss aversion considers mug purchases as gains. It therefore predicts the willingness to pay of owner-buyers to be equal to that of non-owner-buyers. By contrast, psychological ownership theory suggests that once an individual feels ownership for an object, her preference for that object and hence her valuation increases. Accordingly, the valuation of owner-buyers should be equal to that of owner-sellers. The authors also include a condition (non-owner-pair-buyers) to control for diminishing marginal utility and for complementarity. Corresponding participants had to choose between two identical mugs or a varying amount of money. If owner-buyers valued the second mug less than non-owner-buyers valued their first, this would support prospect theory and loss aversion as an explanation for the endowment effect. However, this could also be the result of participants valuing the second mug less than the first because of diminishing marginal utility for mugs. Inversely, if owner-buyers valued a pair of mugs more than twice as much as non-owner-buyers valued a single mug, one could prematurely endorse psychological ownership as explaining theory for the endowment effect. Yet owner-buyers with a strong preference for possessing two complementing mugs would yield the same outcome.

is predicted by ownership status but not by loss aversion (which would be the explanation on the basis of prospect theory).[16] A second experiment where buyers and sellers acted as brokers without owning the object further corroborated these results.

Given these findings, Ericson and Fuster (2014, p. 575) consider psychological ownership relevant for economic research. Psychological ownership seems to increase consumers' valuations. I therefore argue that psychological ownership and corresponding evidence can provide predictions for how distinct income sources might be valued and used. Income sources might evoke feelings of ownership to varying degrees and therefore affect preferences and induce variations in decision making. Psychological ownership can help to predict these variations and thus provides an explanation for violations of fungibility.

To the best of my knowledge, this is the first study that suggests psychological ownership as account for violations of fungibility. So far, authors have argued that prospect theory might serve as an explanation (Epley et al., 2006; Kahneman et al., 1990). However, the evidence by Reb and Connolly (2007) and Morewedge et al. (2009) calls for a theoretical approach that considers psychological ownership.

Utility effects of psychological ownership

Consumption utility Due to trade and the invention of money as a means of exchange, people are rarely the producers of their own consumption goods. Instead, they invest time and effort at work to earn income. These earnings can then be transformed into consumption goods. Besides that, there are many other income sources that are, with varying degrees, less reliant on personal input (dividends, governmental transfers, inheritance). Due to preceding non-monetary investments, earned income might induce a stronger sensation of ownership. As money serves as an intermediary, this suggests that decision makers might be more willing convert money they psychologically own into their own and immediate satisfaction. On the other hand, resources that do not produce feelings of ownership might be more likely to be spent on goods benefiting others or future incarna-

[16] Furthermore, the authors rule out complementarity and diminishing marginal utility for mugs, the objects used. Per-unit valuations of participants who had to choose between two identical mugs or a varying amount of money (non-owner-pair-buyers) were equal to those of non-owner-buyers and smaller than those of owner-buyers.

tions of oneself (c.f. Carrillo and Mariotti, 2000). In the latter case, expenditure is easier to devote to purposes with less guaranteed personal satisfaction, e.g. altruistic or riskier investments. Furthermore, income with weaker feelings of ownership might be more likely to be subject to external influences regarding its allocation. If individuals do not feel the entire ownership of an income, they might respond more closely to recommendations (e.g. labels) on how to expend the income (even if they are actually free in their decision).

Income utility Besides the impact of income composition on consumption preferences, psychological ownership induces a second channel through which income composition can affect utility. It suggests that people also derive varying degrees of utility from the receipt of different income sources. In addition to utility from consuming goods, people derive utility from the acquisition of possessions (Formanek, 1991; Beggan, 1992). This is not limited to the acquisition of final goods. They also enjoy anticipating certain purchases (Loewenstein, 1987). This anticipation feels more real and probably more intense if the corresponding amount of money is already available. Consequently, the receipt of money itself can give pleasure. It allows individuals to anticipate concrete purchases in the future, and provides the prospect of future undetermined purchases including the future anticipation of these (Litwinski, 1947). Considering the receipt of income as a growth in possessions might induce feelings of ownership similar to consumption goods. Income sources that are the returns on non-monetary investments and thus evoke these feelings of ownership more intensely might also be valued more than other sources.

I.3. Model

I.3.1. Consumer choice with source-dependent preferences

Source-dependent preference relations

In the following, I incorporate the insights from psychological ownership theory into consumer choice theory[17] to allow for source-dependent preferences.[18] As with most beha-

[17] I consider consumer choice theory as laid out by Mas-Colell et al. (1995, Chapters 1-3).
[18] See Putler (1992) for a similar approach with reference price effects.

vioural approaches to individual decision making, relaxing the assumption of fungibility sometimes leads to a departure from conventional consumer choice theory (Rabin, 2013).

Consider an agent with incomes I_n and sum of total income $S = \sum_{n=1}^{N} I_n$. Let $I \in \mathcal{I}$ be the *income composition vector* of N income sources with the corresponding income levels $I_1, ..., I_N$, where $\mathcal{I}$ is the set of all non-negative income compositions: $\mathcal{I} = \mathbb{R}_{+}^{N} = \{I \in \mathbb{R}^N : I_n \geq 0 \text{ for } n = 1, ..., N\}$. s is defined as the *relative income composition vector* of the corresponding relative income shares out of total income $s_n = \frac{I_n}{S}$.

$$I = \begin{bmatrix} I_1 \\ \vdots \\ I_N \end{bmatrix}, \quad s = \begin{bmatrix} s_1 \\ \vdots \\ s_N \end{bmatrix} = \begin{bmatrix} \frac{I_1}{S} \\ \vdots \\ \frac{I_N}{S} \end{bmatrix}.$$

The agent spends her income on a bundle of consumption goods $x = (x_1, ..., x_M) \in \mathcal{X}$ at prices $p = (p_1, ..., p_n)$, where $\mathcal{X}$ is the convex set of all non-negative consumption bundles: $\mathcal{X} = \mathbb{R}_{+}^{M} = \{x \in \mathbb{R}^M : x_m \geq 0 \text{ for } m = 1, ..., M\}$. The agent derives utility from consuming x. If she is rational in the classical sense, I denote her utility function as $U(x)$ and can formulate the standard consumer choice problem $\max_{x \geq 0} U(x)$ s.t. $px \leq S$ with the solutions $x^*(p, S)$ and the indirect utility $V(p, S)$. However, this standard model fails to cover a crucial aspect of behaviour by implicitly assuming the fungibility of money. Thus, I allow the assumption to be violated. For equally sized budgets, the optimisation of a single utility function subject to the corresponding budget constraints can yield varying outcomes for different compositions of these budgets. In that case, preferences are source dependent.

Definition 1. *An agent exhibits source-dependent preferences if there exists any sum of total income S, a price vector p, and $I, I' \in \mathcal{I}$ with $I \neq I'$, such that $x(p, I) \neq x(p, I')$.*

I continue by introducing a source-dependent preference relation, which I denote by $\succsim_S$. Psychological ownership theory suggests that feelings of ownership are true preferences and should not be considered a bias. Therefore, I will assume that the source-dependent preference relation remains rational in the sense that it provides a *complete* and *conditionally transitive* ranking of possible consumption choices: complete with respect to all goods, and all income levels and sources, and transitive conditional on a given income composition I. Also, I consider choices as the result of rational deliberation,[19] meaning that agents do not regret their decision nor do I distinguish between decision and experience utility. However, I allow the decision maker to systematically violate the assumption of fungibility.[20] For this reason, I will refer to decisions that are the outcome of source-dependent preferences as *source-dependently rational (SD-rational)* as opposed to classical rational consumer choice.

Definition 2. *The preference relation $\succsim_S$ is called source-dependently rational (SD-rational) if it possesses the following two properties:*

(i) Completeness: For all consumption bundles $x, x^{'} \in \mathcal{X}$ and income compositions $I, I^{'} \in \mathcal{I}$, we have that $(x, I) \succsim_S (x^{'}, I^{'})$ or $(x^{'}, I^{'}) \succsim_S (x, I)$ (or both).

(ii) Conditional Transitivity:

a) For all $x, x^{'}, x^{''} \in \mathcal{X}$ and a given income composition $I \in \mathcal{I}$, if $(x, I) \succsim_S (x^{'}, I)$ and $(x^{'}, I) \succsim_S (x^{''}, I)$, then $(x, I) \succsim_S (x^{''}, I)$.

b) For all income compositions $I, I^{'}, I^{''} \in \mathcal{I}$ and a given $x \in \mathcal{X}$, if $(x, I) \succsim_S (x, I^{'})$ and $(x, I^{'}) \succsim_S (x, I^{''})$, then $(x, I) \succsim_S (x, I^{''})$.

Completeness requires that the decision maker has a well-defined preference between any two possible alternatives. While, traditionally, this assumption only concerns goods, I extend it by the dimension of income sources. For that reason, the decision maker must also have a well-defined preference over two income alternatives with each having the same total worth but a different composition.

The fact that transitivity only needs to hold conditionally on a given income composition permits decision makers to reverse decisions once they decide on a different bundle of incomes. However, given one income composition I, it is not possible that a decision maker exhibits preferences that cycle over a sequence of pairwise choices. Since the chosen consumption bundle depends on the available resources and their composition, transitivity with respect to income compositions must hold irrespective of the ultimate decision.

[19]With the exception of Koszegi and Matějka (2018), this feature is new to the mental accounting literature.

[20]Note that only if the violation is systematic, I can consider it a result of individual deliberation.

Based on Definition 2, Proposition 1 summarises the implications for the strict source-dependent preference and indifference relations $\succ_S$ and $\sim_S$.

Proposition 1. *If $\succsim_S$ is SD-rational then:*

(i) $\succ_S$ *is both irreflexive ($(x, I) \succ_S (x, I)$ never holds) and conditionally transitive (if $(x, I) \succ_S (x^{'}, I)$ and $(x^{'}, I) \succ_S (x^{''}, I)$, then $(x, I) \succ_S (x^{''}, I)$, and if $(x, I) \succ_S (x, I^{'})$ and $(x, I^{'}) \succ_S (x, I^{''})$, then $(x, I) \succ_S (x, I^{''})$).*

(ii) $\sim_S$ *is reflexive ($(x, I) \sim_S (x, I)$ for all (x, I)), conditionally transitive (if $(x, I) \sim_S (x^{'}, I)$ and $(x^{'}, I) \sim_S (x^{''}, I)$, then $(x, I) \sim_S (x^{''}, I)$, and if $(x, I) \sim_S (x, I^{'})$ and $(x, I^{'}) \sim_S (x, I^{''})$, then $(x, I) \sim_S (x, I^{''})$)), and symmetric (if $(x, I) \sim_S (x^{'}, I^{'})$, then $(x^{'}, I^{'}) \sim_S (x, I)$).*

(iii) if $(x, I) \succ_S (x^{'}, I) \sim_S (x^{''}, I)$, then $(x, I) \succ_S (x^{''}, I)$, and if $(x, I) \succ_S (x, I^{'})$ and $(x, I^{'}) \succsim_S (x, I^{''})$, then $(x, I) \succ_S (x, I^{''})$)).

Proof. See Appendix A.1. $\square$

With Definitions 1 and 2, I can describe source-dependent preference relations with a source-dependent utility function.

Definition 3. *A function $U^S : (\mathcal{X}, \mathcal{I}) \to \mathbb{R}$ is a utility function representing source-dependent preference relation $\succsim_S$ if, for all $x, x^{'} \in \mathcal{X}$ and a given income composition $I \in \mathcal{I}$,*

$$(x, I) \succsim_S (x^{'}, I) \Leftrightarrow u(x, I) \geq u(x^{'}, I),$$

and if, for all $I, I^{'} \in \mathcal{I}$ and a given consumption bundle $x \in \mathcal{X}$,

$$(x, I) \succsim_S (x, I^{'}) \Leftrightarrow u(x, I) \geq u(x, I^{'}).$$

Proposition 2. *A preference relation $\succsim_S$ can be represented by a utility function only if it is SD-rational.*

Proof. See Appendix A.2. $\square$

The Walrasian demand function, as introduced in standard microeconomics, assigns one chosen consumption vector x for a given price-income pair (p, S) (Mas-Colell et al., 1995, p. 23). If price-income pairs (p, S) can be assigned to more than one chosen consumption vector, the relation is referred to as Walrasian demand correspondence. In the classical model, it is assumed to be homogeneous of degree zero. Hence, if both prices and income change in the same proportion, then the individual's consumption choice is unaffected (Mas-Colell et al., 1995, p. 23). Due to the nature of the source-dependent preference relations, multiple consumption bundles may be chosen for a given price-income pair (p, S) with distinct income compositions ($S = S^{'}$ and $I \neq I^{'}$). For that reason, analogous to the classical model, the Walrasian demand correspondence for a source-dependent preference relation is homogeneous of degree zero if all prices and all incomes change in the same proportion. I therefore refer to this as conditional homogeneity.

Definition 4. *The Walrasian demand correspondence $x(p, I)$ is conditionally homogeneous of degree zero if $x(\alpha p, \alpha I) = x(p, I)$ for any p, I, and $\alpha > 0$.*

Note that not only the sum of total income S but the entire vector of incomes I is multiplied by α. For the common homogeneity assumption, it suffices that total income and prices increase by the same proportion. However, with source-dependent preferences, an increase of only one income source may change consumption choice.

Walras' law – the assumption that the consumer fully expends her income (including for future consumption) – must not be adjusted to accommodate source-dependent preference relations.

Definition 5. *The Walrasian demand correspondence $x(p, I)$ satisfies Walras' law if for $p \gg 0$ and $I > 0$, we have $px = \sum_{n=1}^{N} I_n$ for all $x \in x(p, I)$.*

Comparative statics

Allowing consumption choices to be dependent on the source and the composition of the available income has important implications for comparative statics. In the following, I demonstrate where the assumption of fungibility and its relaxation produce different results. One crucial aspect is that income effects depend on which income changes. An increase in total income of ΔS, with income composition being constant, can have a different effect on consumption than an increase of one specific income source I_n by the same amount. It is possible that goods appear to be normal when only one income source that is associated with x_n increases but inferior when all income sources increase simultaneously and proportionally. Consequently, also Engel functions that show how the consumption of a good x_n increases with an increase of income can be computed for an increase of income in general with income composition being constant, for an increase of one income source only, and for income changes that lie between those two extremes.

I summarise this result in Proposition 3.

Proposition 3. *If the Walrasian demand function $x(p, I)$ is conditionally homogeneous of degree zero, then for all p and I:*

$$\begin{gathered}\sum_{\ell=1}^{M} \frac{\partial x_m(p,I)}{\partial p_\ell} p_\ell + \frac{\partial x_m(p,I)}{\partial S} S = 0 \quad \textit{for } m = 1, ..., M \\ \textit{if } \frac{\partial I_n}{\partial S}\frac{S}{I_n} = \frac{\partial I_\ell}{\partial S}\frac{S}{I_\ell} \quad \textit{for all } n, \ell.\end{gathered} \tag{I.1}$$

If the condition $\frac{\partial I_n}{\partial S}\frac{S}{I_n} = \frac{\partial I_\ell}{\partial S}\frac{S}{I_\ell}$ does not hold for all n, ℓ, then, in the case of source-dependent preferences, Equation I.1 is positive for goods associated with income sources that increase more and negative for at least one of the remaining goods.

By contrast, two properties hold regardless of source dependence. According to Definition 5, $px = \sum_{n=1}^{N} I_n$ for all p and I. Differentiating this expression with respect to prices and total income yields two results. Total expenditure cannot change in response to price changes (Proposition 4) and must change by an amount equal to any income change (Proposition 5). These are the properties of the Cournot and Engel aggregation, respectively (c.f. Mas-Colell et al., 1995, p. 28).

Proposition 4. *If the Walrasian demand function $x(p, I)$ satisfies Walras' law, then for all p and I:*

$$\sum_{m=1}^{M} p_m \frac{\partial x_m(p,I)}{\partial p_\ell} + x_\ell(p,I) = 0 \quad \textit{for } \ell = 1, ..., M.$$

Proposition 5. *If the Walrasian demand function $x(p, I)$ satisfies Walras' law, then for all p and I:*

$$\sum_{m=1}^{M} p_m \frac{\partial x_m(p,I)}{\partial S} = 1.$$

Basic properties

For the source-dependent preference relation, the common assumptions of (strong) monotonicity (Definition 6) or at least non-satiation (Definition 7), and (strict) convexity (Definition 8 and Definition 9) are in part analogous to the classical model. It is reasonable that consumers prefer larger amounts of a consumption good over smaller ones and have an inclination for diversification. While monotonicity seems to be a realistic assumption for income – more money is always better,[21] convexity perhaps is not. However, neither is concavity. I cannot find any reason why decision makers should always prefer multiple income sources over one or vice versa. Note that income risk might in fact be a reason for diversification, but only due to the consumption risk that goes along with it.

Definition 6. *The preference relation $\succsim_S$ on $(\mathcal{X}, \mathcal{I})$ is monotone if $x \in \mathcal{X}$ and $x^{'} \gg x$ implies $x^{'} \succ_S x$, and $I^{'} \gg I$ implies $I^{'} \succ_S I$. It is strongly monotone if $x^{'} \geq x$ and $x^{'} \neq x$ imply that $x^{'} \succ_S x$, and $I^{'} \geq I$ and $I^{'} \neq I$ imply that $I^{'} \succ_S I$.*

Definition 7. *The preference relation $\succsim_S$ on $(\mathcal{X}, \mathcal{I})$ is locally non-satiated if for every $x \in \mathcal{X}$ and every $\epsilon > 0$, there is $x^{'} \in \mathcal{X}$ such that $\|x^{'} - x\| \leq \epsilon$ and $x^{'} \succ_S x$, and if for every I and every $\zeta > 0$, there is $I^{'}$ such that $\|I^{'} - I\| \leq \zeta$ and $I^{'} \succsim_S I$.*

Definition 8. *The preference relation $\succsim_S$ on $(\mathcal{X}, \mathcal{I})$ is conditionally convex in consumption if for every $x \in \mathcal{X}$ and for a given $I \in \mathcal{I}$, the upper contour set $x^{'} \in \mathcal{X} : (x^{'}, I) \succsim_S (x, I)$*

[21] In theory, it may even be that an agent appreciates the extended consumption possibilities that come with more money, but dislikes certain types of money for things they represent. Dirty money extends consumption possibilities, but the agent might prefer to spend clean money. For example, Morewedge et al. (2018) find that people "actively seek out opportunities" to mentally launder money. That is they exploit occasions to relabel money, which justifies them spending it less virtuously. They even do so if mental money laundering is costly. Income issued by the government also allows for further consumption, but consumers might prefer spending earned income. One can disentangle these considerations when incorporating the means of expenditure into the preference relation. One would observe take-up if the additional-consumption effect dominates and non-take-up if the dirty-money effect dominates.

is convex; that is if $(x^{'}, I) \succsim_S (x, I)$ *and* $(x^{''}, I) \succsim_S (x, I)$*, then* $(\alpha x^{'} + (1-\alpha)x^{''}, I) \succsim_S (x, I)$ *for any* $\alpha \in [0, 1]$.

Definition 9. *The preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is conditionally strictly convex in consumption if for every* $x \in \mathcal{X}$ *and a given* $I \in \mathcal{I}$*, we have that* $(x^{'}, I) \succsim_S (x, I)$*,* $(x^{''}, I) \succsim_S (x, I)$*, and* $(x^{'}, I) \neq (x^{''}, I)$ *implies* $(\alpha x^{'} + (1-\alpha)x^{''}, I) \succ_S (x, I)$ *for all* $\alpha \in (0, 1)$.

Two properties that are particularly relevant for econometric purposes are homotheticity and quasi-linearity (Mas-Colell et al., 1995, p. 45). For source-dependent preferences over two goods, it is possible to draw indifference curves in a two-dimensional space of consumption. However, it is more meaningful to add an income dimension to capture the effects of income composition. I define the preference relation to be conditionally homothetic if all indifference sets for a given income composition are related to proportional expansion along rays in the space of consumption, and homothetic if all indifference sets are related to proportional expansion along rays in the consumption-income space.

Definition 10. *The preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is conditionally homothetic if all indifference sets for a given income composition are related to proportional expansion along rays; that is if* $(x, s) \sim_S (x^{'}, s)$*, then* $(\alpha x, s) \sim_S (\alpha x^{'}, s^{'})$ *for any* $\alpha \geq 0$.

Definition 11. *The preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is homothetic if all indifference sets are related to proportional expansion along rays; that is if* $(x, s) \sim_S (x^{'}, s^{'})$*, then* $(\alpha x, s) \sim_S (\alpha x^{'}, s^{'})$ *for any* $\alpha \geq 0$.

With source-dependent preferences, quasi-linear source-dependent preferences are particularly interesting.

Definition 12. *The preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is quasi-linear with respect to good 1 (called, in this case, the numeraire good) if*

(i) All the indifference sets are parallel displacements of each other along the axis of good 1. That is, if $(x, I) \sim_S (x^{'}, I)$*, then* $(x + \alpha e_1, I) \sim_S (x^{'} + \alpha e_1, I)$ *for* $e_1 = (1, 0, ..., 0)$ *and any* $\alpha \in \mathbb{R}$.

(ii) *Good 1 is desirable; that is* $(x + \alpha e_1, I) \succ_S (x, I)$ *for all* $x, \alpha > 0$.

The case of source-dependent preferences does not allow the numeraire good to be interpreted as money as is sometimes done (e.g. Brekke, 1997). This is because the source of money determines its psychological value. Therefore, the numeraire can only be interpreted as the consumption of all goods other than those under consideration.[22]

Source-dependent utility functions

The assumption of continuity of $\succsim_S$ guarantees the existence of a functional representation of the source-dependent preference relation, a continuous source-dependent utility function.

Definition 13. *The preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is continuous if it is preserved under limits. That is, for any sequence of pairs* $\left\{(x^n, I^n), (x'^n, I'^n)\right\}_{n=1}^{\infty}$ *with* $(x^n, I^n) \succsim_S (x'^n, I'^n)$ *for all* n, $(x, I) = \lim_{n\to\infty}(x^n, I^n)$, *and* $(x', I') = \lim_{n\to\infty}(x'^n, I'^n)$, *we have* $(x, I) \succsim_S (x', I')$.

Proposition 6. *Suppose that the rational preference relation* $\succsim_S$ *on* $(\mathcal{X}, \mathcal{I})$ *is continuous. Then there is a continuous utility function* $U^S(x, I)$ *that represents* $\succsim_S$.

Proof. See Appendix A.3. □

Utility maximisation

Finally, if U^S is continuous, we can set up the consumer's decision problem and compute her optimal choice by maximising her source-dependent utility function subject to her budget constraint.

Proposition 7. *If* $p \gg 0$ *and* $U^S(\cdot)$ *is continuous, then the utility maximisation problem has a solution.*

Proof. See Appendix A.4. □

[22] This is also the interpretation of numeraire goods in standard textbooks (c.f. Mas-Colell et al., 1995, p. 311)

Source sensitivity

Source-dependent preference relations as described here cannot be represented by familiar utility functions. I allow income and its sources to affect consumption utility as well as overall utility through a rational decision process. Therefore, a utility function must contain income in some form. This has already been captured in the previous sections with utility being a function of vectors of consumption x and income composition I. However, people do not only vary in their preferences for goods, but also in the extent to which they exhibit behavioural patterns and biases. One will not observe the same degree of source dependence for all individuals. For that reason, I define the tendency to which individuals are honouring the composition of income as source sensitivity.

Definition 14. *Source sensitivity $\sigma \in [0, \infty)$ is defined as the extent to which a change in the composition of income, $I \neq I^{'}$, affects the consumption bundle x and utility V if that change does not affect total income, $S = S^{'}$. If an individual is source insensitive, x^* is independent of the composition of income, that is her preferences are not source dependent.*

Hence, if the agent is source insensitive ($\sigma = 0$), or rational in the classical economic sense, she will always choose the very same consumption bundle irrespective of the sources of income and their shares of the total income. Analogously, the agent is source sensitive ($\sigma > 0$) if she prefers different outcomes when facing and deciding over the use of different sources of income.

Budget-neutral income changes

I refer to a change in I_n as a budget-neutral change (increase or decrease) if it does not affect total income but only its composition.

Definition 15. *A budget-neutral increase (decrease) of I_n is defined as an increase (decrease) of I_n's share of total income s_n while the sum of total income S as well as the relative shares of all remaining income components out of total income to each other, $\frac{I_j}{S-I_n} = \frac{I_j^{'}}{S-I_n^{'}}$ with $j \neq n$, remain constant.*

Hence, if one income component I_1 changes, the remaining income components $I_{-1} = (I_2, ..., I_n)$ compensate for this change. As a consequence, the shares of all remaining income components out of total income s_{-1} must change. Yet, by definition, the relative shares of all remaining income components out of total income to each other remain constant, i.e. $\frac{I_n}{S-I_1} = \frac{I_n'}{S-I_1'}$.

Allowing income components to affect the utility from consumption implicitly induces preferences over income sources. Consider an individual who has no preferences over income sources, but a budget-neutral increase of income I_k increases her marginal utility from consuming x_k. Then the increase in I_k increases overall utility unless this increase in I_k and the decrease of all remaining income sources decreases the utility from the consumption of other goods. If that is not the case, the individual de facto prefers income I_k over other income sources.

Thus, at the same time as deriving utility from consumption, the individual experiences a psychological cost or benefit from obtaining and expending a certain sources of income. People might feel proud receiving earned income, glad about public transfers, or patronised by being pushed towards the consumption of certain goods when receiving labelled transfers (e.g. child benefits). Income not only constitutes the means to purchase goods, but can also have inherent effects on utility.

Being explicit about preferences over income sources reveals this assumption. Otherwise, the effect of income composition on utility would remain implicit. Thus, I acknowledge that income composition might not only affect marginal utility of consumption, but may also directly affect overall utility. I therefore define the effect of income sources on overall utility to be the vector function $\boldsymbol{\theta}(\sigma, I) = (\theta_1(\sigma, I), ..., \theta_N(\sigma, I))$.

Let further $\boldsymbol{\delta}(\sigma, I) = (\delta_1(\sigma, I), ..., \delta_M(\sigma, I))$ be the vector function that describes how income composition affects the marginal utility of consumption goods. Assuming an additively separable utility function, $\boldsymbol{\delta}$ and $\boldsymbol{\theta}$ are implicitly defined by Definition 16.

Definition 16. $\boldsymbol{\theta}(\sigma, I)$ *and* $\boldsymbol{\delta}(\sigma, I)$ *are implicitly defined by* *(i) the change of the marginal utility from x_m subject to a change in income source I_n*

$$\frac{\partial U^S(x, \boldsymbol{\delta}(\sigma, I), \boldsymbol{\theta}(\sigma, I))}{\partial x_m} = \delta_m \frac{\partial u(x_m)}{\partial x_m}$$

(ii) and the change of U^S subject to a change in income source I_n

$$\frac{\partial U^S(x, \boldsymbol{\delta}(\sigma, I), \boldsymbol{\theta}(\sigma, I))}{\partial I_n} = \sum \left(\frac{\partial \delta_m}{\partial I_n} u(x_m) \right) + \frac{\partial \theta_n}{\partial I_n}.$$

The individual's source-dependent utility U^S is then a function of x, I, and σ.

$$\max_x U^S(x, \boldsymbol{\delta}(\sigma, I), \boldsymbol{\theta}(\sigma, I)) \quad \text{s.t.} \quad S = \sum_{n=1}^{N} I_n \geq px$$

Equivalent income

Knowing the effect of a budget-neutral increase of an income source I_k on the marginal utilities of consuming x and the subject's preferences over income sources, I can find a total income that would result in the same utility as before the increase. I refer to this income as equivalent income S_E (King, 1983).

King (1983, p. 188) defines the equivalent income as the "level of income which, at a reference price vector, affords the same level of utility as can be attained under the given budget constraint". I define the equivalent income for a change to the income composition analogously. For a given price vector p, the equivalent income S_E at a reference income composition s^R is defined by

$$V(p, S_E, s^R) = V(p, S, s).$$

Hence, for constant prices p, S_E is the income with the composition s^R that yields the same utility as the given income S with the composition s. The difference between the original total income level S and the equivalent income S_E provides a measure of welfare loss or gain.

Summary of the basic model and results

This extension to consumer choice theory allows agents to exhibit different preferences for different income sources. Although Loewenstein and Issacharoff (1994) suspect that allowing violations of fungibility might make it difficult to model consumer behaviour, I demonstrate as a first result that consumer theory is still feasible if the assumption of fungibility is relaxed. The model can therefore be used to depict corresponding behaviour.

However, naturally, the extension affects some results of classical consumer theory. With source-dependent preferences, whether an increase of total income is due to all income sources increasing simultaneously or due to the increase of only one income source may alter consumer choice. Therefore, homogeneity applies only on condition that all income sources increase at the same rate. Furthermore, allowing income sources to affect consumer choice and utility restricts the interpretation of a numeraire good to the level of consumption of all goods other than that under consideration and rules out its simple interpretation as "money" (e.g. Brekke, 1997). By contrast, other properties such as those of the Cournot and Engel aggregation are not affected.

For $\sigma \neq 0$, the presented model predicts one element of behaviour which Thaler (1985, 1990, 1999) terms mental accounting. While Thaler (1985, 1990, 1999) provides an idea of how to conceive corresponding activities, the extension in Section I.3.1 formalises one component of this idea: the assignment of funds to goods. This formalisation can be used to integrate conjectures about how this assignment arises. In Section I.2.2, I introduced the psychologically informed rationale that effort increases the valuation of thereby earned objects. Incorporating these insights from psychological ownership into the theoretical framework presented in Section I.3.1, I am able to specify a concrete utility function with source-dependent preferences which can be used for calibrations (Section I.4) and applications (Section I.5).

I.3.2. A specification based on psychological ownership

Consider an agent who consumes two normal goods and decides on two income sources. Let x_1 and x_2 be the quantities of the goods and w and τ the two sources of income. Then, a rational agent solves the problem

$$\max_{x_1,x_2} U(x_1, x_2) \quad \text{s.t.} \quad S = \omega + \tau \geq p_1 x_1 + p_2 x_2.$$

with the solutions $x_1^*(S, p_1, p_2)$, $x_2^*(S, p_1, p_2)$, and $V(S, p_1, p_2)$.[23]

Now let the agent be source sensitive. To have two income sources with varying attributes, assume that income ω is earned and follows preceding non-monetary investments whereas income τ is unearned. Given the research discussed in Section I.2.2, this suggests two consequences. First, due to a stronger sensation of psychological ownership evoked by earned income, the agent prefers spending ω. As also speculated by Loewenstein and Issacharoff (1994, p. 166), people might generally appreciate purchases made with earned money to a greater extent, exhibiting a preference for wage rather than transfer payments. With a given source sensitivity σ, assume that the agent's utility increases with the relative share of earned income ω out of total income $S = \omega + \tau$. Second, income ω might be more strongly associated with certain goods than income τ. In Section I.2.2, I discuss how unearned income might be more likely to be spent pro-socially due to its lack of psychological ownership. Assume that x_2 represents such a pro-social consumption good (e.g. a donation). Alternatively, τ could be a labelled governmental transfer targeted on x_2. The lack of psychological ownership experienced with this transfer makes the agent more willing to associate τ with the targeted good x_2. Hence, a source-sensitive agent exhibits a stronger preference for x_2 when spending τ. Correspondingly, let the marginal utility from x_2 increase with the relative share of un-earned income τ out of total income S. With a given budget constraint, it is straightforward that this also indirectly affects the consumption of x_1.

[23] Analogue to Proposition 7, the solution exists if $p_1, p_2 > 0$ and $U(\cdot)$ is continuous.

Based on these considerations, I specify the concrete consumer choice problem as

$$\max_{x_1,x_2} U^S(x_1, x_2, \delta(\sigma,\omega,\tau), \theta(\sigma,\omega,\tau)) = u(x_1) + \left(1+\sigma\frac{\tau}{\omega+\tau}\right) v(x_2) + \sigma\frac{\omega}{\omega+\tau}$$
$$\text{s.t.} \quad S = \omega + \tau \geq p_1 x_1 + p_2 x_2. \tag{I.2}$$

By Proposition 7, this utility maximisation problem has a solution. The specification possesses the following characteristics. First, a rise in income source τ increases the marginal utility the individual experiences from consuming x_2. Hence, even if total income and prices remain constant, an increasing fraction of τ in total income will lead to an increased consumption of x_2. Second, the decision maker prefers to decide on earned income. Her income utility $\theta(\sigma,\omega,\tau)$ increases with the fraction $\frac{\omega}{S}$. Depending on the functional form of $v(x_2)$, utility can increase or decrease with a budget-neutral increase in τ.

As a result, in situations that are identical in the standard economic sense, but in which the agent's income is composed differently, one will observe different choices. The incorporation of income attributes into the utility function predicts the agent to behave as if income τ (at least partially) constituted the budget for consumption of x_2. This is one component of operations Thaler (1985, 1990, 1999) refers to as mental accounting.

With Specification I.2 at hand, it is convenient to graphically illustrate source-dependent behaviour and exemplify the corresponding equivalent income. Figure I.1 shows how a budget-neutral change in the composition of the agent's income affects her optimal consumption decision. The figure depicts a budget constraint and a two-dimensional projection of two cross sections of the corresponding indifference set. In the initial situation with income S, the agent consumes bundle (x_1^S, x_2^S). Now consider a budget-neutral increase in τ, that is a simultaneous increase of τ and decrease of w that completely balance. Hence, $S = S'$. With constant total income and prices, a rational individual would always choose (x_1^*, x_2^*). However, if she is source sensitive, she will devote a larger fraction of her income to the consumption of x_2 which she associates with the income source τ. As x_2^S increases to $x_2^{S'}$, she must reduce the consumption of x_1^S to $x_1^{S'}$.

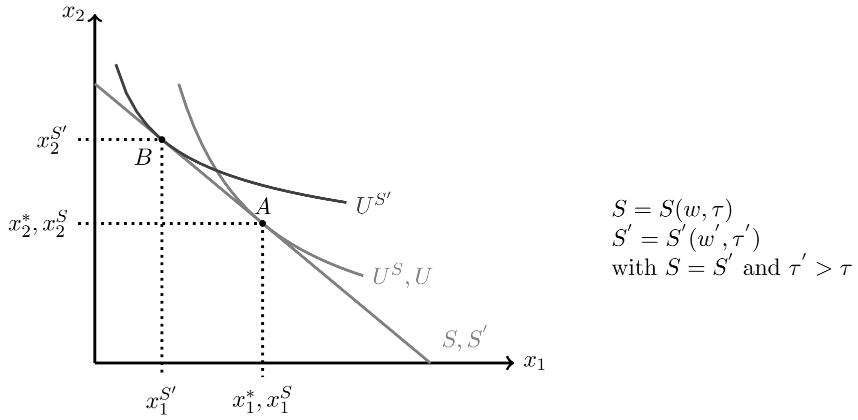


Figure I.1.: Optimal consumption bundle before and after a change of the composition of income with source-dependent preferences.

Bear in mind that the original consumption set (x_1^S, x_2^S) would still be feasible. However, the increase of income source τ prompts the source-sensitive consumer to choose another consumption bundle.

Although Figure I.1 suggests differently, one in fact does not obtain intersecting indifference curves. Instead, the incorporation of a third dimension, income composition, allows for the construction of indifference sets that represent combinations of bundles and income compositions with the same utility level.

Finally, the equivalent income S_E can be computed by calculating the consumption costs of x_1^E and x_2^E that yield the utility $V(p, S, s)$, with $s = \left(\frac{\omega'}{S}, \frac{\tau'}{S}\right)$, but would have been chosen given the old income composition $s^R = \left(\frac{\omega}{S}, \frac{\tau}{S}\right)$.

I.4. Empirical evidence

I.4.1. Source-dependent consumption utility

Specification I.2 can account for various findings. It predicts that income associated with strong feelings of psychological ownership, whether promoted by legal ownership or not, raises the individual's expectation to remain the owner of the income or beneficiary of the consumption associated with it. Due to the invested effort, earned income should be less likely to be donated, a prediction supported by experimental studies using dictator games

(Cherry, 2001; Cherry et al., 2002; Carlsson et al., 2013). For example, Cherry (2001) and Carlsson et al. (2013) find that individuals who have to decide how much money to give to another participant or charity only give half as much when deciding over earned money in comparison to allocated money. In the laboratory experiment conducted by Cherry (2001) in the United States, giving decreases from 30.8 percent to 16.4 percent. In Carlsson et al. (2013), who conducted a laboratory and a field experiment in China, giving decreases from 74 to 29 percent in the laboratory, and from 37 to 19 percent in the field.

These findings can be explained by two effects. The receipt of earned income must either increase the marginal utility of one's own pay-off, or decrease the marginal utility of allocating money to another participant. While classical theory of consumer choice fails to account for this behaviour, it can be accommodated by a theory of consumer choice with source-dependent preference. Let the decision maker solve the following optimisation problem[24]:

$$\begin{aligned} \max_{x_1,x_2} U^S(x_1,x_2) &= \ln(x_1) + \delta(\sigma,\omega,\tau)\cdot\alpha_{1,2}\cdot\ln(x_2) + \theta(\sigma,\omega,\tau) \\ \text{s.t. } \omega+\tau &= x_1+x_2, \end{aligned} \tag{I.3}$$

with $\alpha_{1,2}$ being the degree of altruism of the subject towards the recipient, and x_1 and x_2 the amounts of money allocated by the subject to herself and the recipient, respectively. Further, assume the functional form of $\delta(\sigma,\omega,\tau)$ to be $\delta(\sigma,\omega,\tau) = (1+\sigma\frac{\tau}{\tau+\omega})$. Hence, $U^S(x_1,x_2) = \ln(x_1) + (1+\sigma\frac{\tau}{\tau+\omega})\cdot\alpha_{1,2}\cdot\ln(x_2) + \theta(\sigma,\omega,\tau)$. Calibration to the laboratory results from Cherry (2001) gives an average subject's degree of altruism of $\alpha_{1,2} = 0.20$, and a σ of 1.27. Similarly, a calibration to the results of Carlsson et al. (2013) gives $\alpha_{1,2} = 0.23$ and $\sigma = 1.50$ in the field, and $\alpha_{1,2} = 0.41$ and $\sigma = 5.97$ in the laboratory experiment.

Kooreman (2000) finds that the marginal propensity to purchase children's clothing when using child benefits is more than ten times larger than when using other income

[24] As the calibration exercise requires an explicit solution, I assume logarithmic utility from x_1 and x_2. Logarithmic utility functions are popular in applications as they fulfil the assumptions of strictly increasing utility and decreasing marginal utility (Mas-Colell et al., 1995; Feldstein, 1985). They were first proposed by Bernoulli (1954).

sources (0.113 versus 0.010). A calibration based on the corresponding coefficients (including the constant but excluding controls) gives $\alpha_{1,2} = 0.01$ and $\sigma = 10.48$.[25] In grocery shopping, Milkman and Beshears (2009) find that customers who receive a \$10-off coupon, which on average accounts for 7.56 percent of total spending, spend 1.3 percent more in total and 4.9 percent more on "marginal" goods (goods they have not purchased before and would not purchase again in the data set). To distinguish contexts, I replace the degree of altruism $\alpha_{1,2}$ in Specification (I.3) with β. With x_1 being non-marginal and x_2 being marginal goods, $\beta = 0.35$ and $\sigma = 0.60$. Hastings and Shapiro (2018) find that benefits from the US Supplemental Nutrition Assistance Program (SNAP, U.S. Department of Agriculture, 2018) on average increase spending on SNAP-eligible goods by \$110. Assuming a monthly household income of \$4,513 and SNAP benefits of \$196.90 as well as \$355 spending on SNAP-eligible goods without and \$465 with SNAP benefits yields $\beta = 0.09$ and $\sigma = 6.77$. The calibrated values (including calibrations for Boca and Flinn, 1994 and Hener, 2017) of σ and their associated share of unearned income are summarised in Figure I.2. The relationship between the shares of transfers and corresponding responses suggests that relatively small transfers are particularly effective. This presents an argument in favour of multiple small targeted transfers rather than a single large one.

In contrast to $\delta(\sigma, \omega, \tau)$, individuals' utility levels from different income sources cannot be determined from existing results. It would require a tailored experimental design that

[25] Note that the degree of altruism is only based on the expenditures on children's clothing. It is unlikely that clothing is the only product parents buy for their children, let alone the only way they can express their altruistic feelings towards their children. Furthermore, the calibrated σ seems quite large. But the calibration only yields a point estimate for σ and is based on the assumption that σ is linear and constant with respect to the fraction of child benefits to total income. However, in the respective sample, child benefits represent only 2.5 percent of total net income. It seems likely that σ decreases in this fraction, suggesting a non-linear relationship. This is supported by an analogous calibration (including the constant but not controls) using the estimation results of Boca and Flinn (1994) where alimony payments to the mother represent ten percent of her total income and I obtain parameters of $\alpha_{1,2} = 0.01$ and $\sigma = 2.33$ for child clothing. In Hener (2017), child benefits on average only constitute 0.08 to 0.47 percent of household net income (depending on the number of children). A calibration with figures from the summary statistics (due to the lack of predicted values; yet the summary statistics even suggest a weaker source sensitivity than the actual difference-in-differences model) gives $\alpha_{1,2} = 0.01$ and $\sigma = 281.50$ with x_2 being the sum of all child-assignable consumption, and $\alpha_{1,2} = 0.02$ and $\sigma = 375.92$ with x_2 being contributions to housing savings plans, which Hener (2017) also considers beneficial to children, also suggesting a higher sensitivity to changes in the income composition when the composition is more imbalanced. Combining all available child-assignable consumption goods and contributions to the housing savings plan yields $\alpha_{1,2} = 0.03$ and $\sigma = 363.76$.

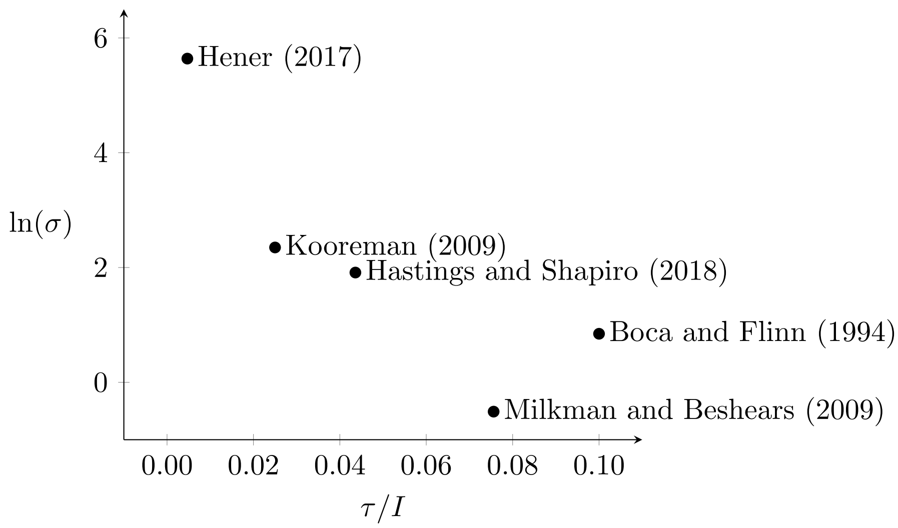


Figure I.2.: Share of unearned income and logarithm of calibrated σ.

elicits the valuations for unearned and earned endowment. By Definition 16, one could then compute $\theta(\sigma, \omega, \tau)$.

Similarly to the results obtained in dictator games, psychological ownership also seems to matter in more complex experimental designs and outside the laboratory. Hoffman and Spitzer (1985) and Balafoutas et al. (2013) observe that subjects who have to invest (effort or money) into receiving a certain outcome feel more entitled to enjoy its benefits and therefore vote for less redistribution. Furthermore, recent studies that investigate consumption choice upon the receipt of bequests (Zagorsky, 2013) and lottery gains (Briggs et al., 2015) observe increased saving rates and higher stock market participation, respectively. Both can be considered generous behaviour towards future incarnations of oneself.

Additionally, psychological ownership suggests that preceding investments increase the utility people derive from consumption, a feature incorporated into theory of consumer choice with source-dependent preferences. In fact, Loewenstein and Issacharoff (1994) experimentally establish that subjects value goods more if they believe they had obtained them because of their own performance rather than luck. The experiments conducted by Norton et al. (2012) substantiate this finding. The authors find that when a product has been successfully assembled by an individual herself, her valuation of the object increases.

I.4.2. Source-dependent income utility

Humans derive utility from growth in possessions (Formanek, 1991; Beggan, 1992). In addition, Bateman et al. (2005) find that, before they transform money into goods, people can perceive money as a kind of object. They can exhibit the endowment effect with money. This suggests they might derive utility from the possession of money. Since, according to psychological ownership theory, invested effort strengthens feelings of ownership, this would imply that utility from earned income is higher than that of unearned income – a prediction that is also supported empirically. DeVoe et al. (2013) find that individuals place greater importance on money when they receive income from labour than when they receive non-labour income. Also, there is indicative evidence that unearned income increases life satisfaction less than earned income (Petilliot, 2017).

Furthermore, Kassenboehmer and Haisken-DeNew (2009) find that, for a given and constant income, an increase of the income share of social assistance payments significantly decreases life satisfaction. Here, not only the extensive margin matters, that is whether one has to rely on social assistance or not, but also the intensive margin, meaning which fraction of income is unearned. Similarly, the authors show that an increase in social assistance payments, which also increases total income, is associated with an increase in life satisfaction, yet not as much as an increase in labour income. One explanation for this effect is social stigma (reputation effects, Akerlof, 1980), which would not represent a violation of fungibility. However, it is possible that decreased feelings of ownership are jointly responsible for corresponding effects. Further research is necessary to disentangle these two effects. Interestingly, the receipt of child benefits increases life satisfaction beyond pure income effects. Kassenboehmer and Haisken-DeNew (2009) do not provide an explanation for this finding, yet they only measure ultimate life satisfaction that proxies utility. People could in fact still prefer earned income over child benefits. But this effect is outweighed by a larger increase of marginal utility from purchasing child-related products.

I.5. Positive externalities and redistribution

Next, I discuss an investigation of redistribution with labelled but non-earmarked transfers. Labelled transfers have been shown to be particularly susceptible to violations of fungibility. Studies found source-dependent consumption responses for child benefits (Kooreman, 2000; Blow et al., 2012; Hener, 2017)[26] and alimony payments (Boca and Flinn, 1994), labelled cash transfers for education (Benhassine et al., 2015), and lump-sum transfers as governmental stimuli (Buddelmeyer and Peyton, 2014).

I.5.1. Set-up

Consider an agent i. For simplicity I assume only one active decision maker. For the sake of notation I omit the index for i. The agent consumes a numeraire good x, leisure $l \in [0,1]$, and a good g that has a positive externality on others that are denoted by $-i$. To that end, she works $(1-l)$ and earns a net income of $(1-t)(1-l)\omega$ plus, possibly, a transfer τ. Assume that she enjoys consuming g up to a certain socially inefficient amount, but not beyond.[27] For simplicity, all prices are normalised to one.

The agent's consumption problem[28] is

$$\begin{aligned} \max_{x,l,g} \quad U^S(x,l,g) =& x + \ln(l) + (1+\sigma\tau)\ln(g) + \sigma(1-t)(1-l)\omega \\ \text{s.t.} \quad S =& (1-t)(1-l)\omega + \tau = x + g. \end{aligned} \tag{I.4}$$

The utility of any other individual is $U_{-i}(g) = \ln(g)$.

Since the social planner takes into account the behavioural response function of the consumer, she faces a two-stage optimisation problem that can be solved by backwards induction.

[26]In contrast to a majority of studies, Edmonds (2002) does not find that child benefits are spent differently than other income.

[27]Take thermal insulation as an example. The agent benefits from draught-proof windows but does not take into account the positive externality on the environment from additional units of thermal isolation (e.g. elsewhere in the house).

[28]Since with constant total income the term capturing the agent's source dependence $\left(1+\sigma\frac{\tau}{(1-t)(1-l)\omega+\tau}\right) = \left(1+\sigma\frac{\tau}{I}\right)$ is linear in σ, I simplify it to $(1+\sigma\tau)$. Note that the resulting utility function is not conditionally homogeneous of degree zero as defined in Definition 4.

I.5.2. Consumer

For completeness, note that without any governmental intervention ($t = \tau = 0$) the consumer's maximisation problem collapses to

$$\begin{aligned} U(x, l, g) =& x + \ln(l) + \ln(g) + \sigma(1 - l)\omega \\ \text{s.t.} \quad S =& (1 - l)\omega = x + g. \end{aligned}$$

The consumer only has one income at hand and will consume g without interference by the social planner. The solutions to x^*, l^*, and g^* are straightforward.

However, the social planner might want to maximise overall welfare and therefore increase consumption of the good g. To this end, she collects revenue with the help of a proportional income tax t. The tax is subsequently redistributed as a labelled transfer τ. Due to its label (e.g. a note to the payee) and a lack of psychological ownership, individuals with source-dependent preferences, are more likely to spend τ on the targeted product g. Solving the consumer optimisation problem I.4 yields the indirect utility

$$\begin{aligned} V(\omega, \tau, t) =& \underbrace{\frac{\omega - \sigma + \tau + \omega\sigma - \omega t - \sigma^2\tau - \omega\sigma t - 2}{1 + \sigma}}_{x^*} + \\ &+ \ln\left(\underbrace{\frac{1}{\omega\,(1 + \sigma)\,(1 - t)}}_{l^*}\right) + \\ &+ (1 + \sigma\tau)\ln(\underbrace{1 + \sigma\tau}_{g^*}) + \underbrace{\frac{\omega\sigma\,(1 + \sigma)\,(1 - t) - \sigma}{(1 + \sigma)}}_{\text{Utility from income}}. \end{aligned} \tag{I.5}$$

As U_{-i} only depends on how much agent i purchases g, $-i$'s indirect utility is

$$V_{-i}(\omega, \tau, t) = \ln(1 + \sigma\tau).$$

I.5.3. Social planner

Let the social planner be limited by a balanced budget. She thus faces a budget constraint of $\tau^* = (1 - l^*)t\omega = \left(1 - \frac{1}{\omega(1+\sigma)(1-t)}\right) t\omega$. She chooses t to maximise social welfare and therefore solves the following problem:

$$\max_t \quad W(\tau^*(t)) = V_i(\tau^*(t)) + \epsilon V_{-i}(\tau^*(t))$$

with $\epsilon \geq 0$ being the social planner's weight on the utility of individuals affected by the externality. It can also be interpreted as the extent of the externality. Then, ϵ is larger the more other individuals benefit from the agent's investment into g, or the more individuals are affected by the externality.

The optimal tax rate t^* is then defined by

$$F(t) = \frac{\partial V_i}{\partial t} + \epsilon \frac{\partial V_{-i}}{\partial t} = 0.$$

I begin with a simple result. If the agent is source insensitive and disregards the source of her income, she does not condition her decision regarding the consumption of g on τ. Anticipating that the available policy cannot increase consumption of g but only distorts the agent's labour-supply decision, a redistributive tax will only have distortive effects. Therefore, the social planner does not intervene and sets $t^* = 0$.

Proposition 8. $\sigma = 0 \Rightarrow t^*(\epsilon) = 0 \quad \forall \epsilon \geq 0.$

Proof. See Appendix A.5. □

Now, consider the agent is source sensitive, $\sigma > 0$. In this case the optimal tax will be positive for sufficiently large ω. For very small values of ω, the consumer will not work at all and only consume leisure. As taxation in this case leads to an increase in demand of leisure, taxation is not effective. Consequently, the social planner should not tax, as summarised in Lemma 1.

Lemma 1. $t^*(\omega \leq \underline{\omega}) = 0$ *with* $\underline{\omega} = \frac{1}{(1+\sigma)}$.

Proof. See Appendix A.6. □

As, by assumption, $\sigma \geq 0$, $t \geq 0$ if $\omega \geq 1$. Without loss of generality, one can assume $\omega > 1$ and eliminate the implausible scenario with $l^* = 1$.

The next result emerges from the fact that τ is constrained by the revenues generated by the income tax. As, by assumption, the agent does not take into account that the tax revenue will be redistributed in the form of a lump-sum transfer, she adjusts her labour supply in response to the introduction of a tax. For that reason, an increase in tax at some point will lead to a lower lump-sum transfer. Since a simultaneous increase in t and decrease in τ decreases the agent's utility, this point constitutes an upper bound for the tax. Given $l^*(\sigma, \omega, t)$, this upper bound for the optimal policy is shown in Lemma 2.

Lemma 2. $\bar{t} = 1 - \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}}$.

Proof. See Appendix A.7. □

Due to the positive externality exerted by the consumption of g, the social planner can increase social welfare if she exploits the agent's source sensitivity regarding the consumption of g. This result is summarised in Proposition 9.

Proposition 9. *It is optimal for the social planner to redistribute, hence* $\tau > 0$ *and* $0 < t < 1 - \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}}$, *if* $\sigma > 0$, *and* $\omega > \frac{1}{(1+\sigma)}$.

$$\forall \sigma > 0 : t^*(\epsilon) > 0 \quad \forall \epsilon \overset{!}{\geq} 0, \omega > \frac{1}{(1+\sigma)}$$

Proof. See Appendix A.8. □

With $\epsilon > 0$, redistribution and labelling the transfers increase social welfare. If necessary, it can more than offset the reduction in the agent's utility with higher a consumption of g and thus a higher utility of $-i$. This is in sharp contrast to the classical optimal taxation literature (e.g. Sheshinski, 1972). As shown in Proposition 8, the welfare-maximising tax is zero if the agent is source insensitive.

I.5.4. Discussion

Prospect Theory and spending behaviour

Besides psychological ownership as an explanation for violations of fungibility, economists have brought up other theories to explain behavioural responses to labels. Epley et al. (2006) consider loss aversion and framing as the origin of different behaviour across income sources. In four experiments, Epley et al. (2006) find that income framed as a gain from the status quo (e.g. a bonus, governmental transfer, stimulus) is more likely to be spent than commensurate income framed as a return to the status quo (e.g. a rebate, tax or tuition refund). By contrast, the latter is more likely to be saved. The authors obtain this result for recalled, reported, and recorded spending of subjects. Epley et al. (2006) hypothesise that income that is framed as a gain is more strongly perceived as additional budget and therefore more likely to be spent. While an (unexpected) refund actually increases one's consumption possibilities, it might be considered a returned loss, hence, no additional consumption budget.

As laid out by Epley et al. (2006), prospect theory can help to understand consumer behaviour to some degree. However, this is limited to situations that allow a categorisation of income into perceived gains, returns to the status quo, and losses. Incorporating psychological ownership, the model of source-dependent preferences builds its predictions on the extent to which received income is preceded by (non-monetary) investments. Arguably, this constitutes a more tangible determinant of behaviour than the consumer's perception of income as a gain or loss. Considering both salary and governmental transfer payments as a gain, one would not expect varying behaviour on the basis of prospect theory. Contrarily, psychological ownership correctly predicts a behavioural response as demonstrated with child benefits and earned income in Section I.4.1.

Besides that, Epley et al. (2006) draw on prospect theory to explain variations on the aggregate, namely in the marginal propensity to consume out of income framed as a gain or loss. This chapter, on the other hand, provides a foundation to explain more detailed variations in the composition of consumer choice.

Reciprocity to the payer

I view psychological ownership as introduced in the preceding sections as the psychological root for source-dependent behaviour and responses to labels. However, reciprocity towards the government, which pays out the transfer, could be another reason why we might observe varying spending patterns for earned income and governmental transfers (Hener, 2017). People who receive transfers might want to conform with what they think the government seems to intend with issuing such a stimulus. These preferences then could be represented by preferences for reciprocity (Gouldner, 1960). Corresponding behaviour would therefore not count as violations of fungibility.

Alternatively, recipients could strategically conform to the intended use of governmental transfers. They might anticipate that the payment will be frozen if officials detect that the money is not spent according to its purpose. In order to guarantee a continuation of transfers, recipients comply with how the transfer is labelled. However, if such behaviour comes at a cost (e.g. recipients actually have strong preferences for different goods), strategic compliance could be subject to a free-rider problem. It might therefore not suffice to explain varying spending behaviour over income sources.

I.6. Conclusion

Standard consumer theory assumes that income is fungible by adding all different sources of income to one total. Although economists argue that this assumption is critical (Hastings and Shapiro, 2013), there have only been few attempts to account for source dependence in theories of consumer choice. Building on psychological ownership theory, the model of source-dependent preferences presented in this chapter incorporates such violations of fungibility into theory of consumer choice. Importantly, it makes the effects explicit that income composition can have on consumption preferences as well as total utility.

The chapter provides three contributions to the literature. First, on the basis of insights from research on psychological ownership, it provides a rationale and a model that can explain mental accounting-type behaviour in experiments and the field where choice is affected by the source and composition of income. In contrast to concerns that source-dependent preferences might make consumer choice behaviour more difficult to model (Loewenstein and Issacharoff, 1994), it also demonstrates that this is still feasible. However, one has to bear in mind that certain interpretations (e.g. with respect to numeraire goods) and results (e.g. homogeneity) must be adjusted once one allows source-dependent preferences. While classical models of consumer choice only allow the analysis of effects when total income changes, the present model permits the analysis of effects that are driven by changes of particular income sources. Second, the theoretical formalisation of source-dependent preferences facilitates the comparison of empirical findings that identify violations of fungibility. A qualitative comparison of calibrations based on the responses to governmental transfers suggests that multiple small transfers are more effective and should be preferred over few larger transfers. Third, the approach allows for welfare analyses of public policies that affect the composition of income. In contrast to the classical optimal taxation literature (Sheshinski, 1972), a model with source-dependent preferences suggests that redistribution through labelled transfers can enhance social welfare in the context of consumption externalities. However, it also makes clear that further empirical and experimental investigations are necessary to learn more about preferences over income sources and links between income sources and consumption goods.

How do recipients of public transfers feel and act when they receive and spend allocated money compared to earned income? How do consumption patterns change when households decide over varying sources of income? How does it affect individuals' preferences, consumption, and welfare to decide on the income from dividends, a bonus, or labour income? These are questions to consider when we discuss capital gains and labour income taxation, public transfer programmes like SNAP, or programmes of child benefits, which are particularly popular in Europe,[29] and universal basic income policies as tested in Finland (Kansaneläkelaitos, 2018). Furthermore, sensation of ownership might also

[29] In 2013, EU countries spent 2.3 percent of their GDP (and 8.4 percent of their expenditures on social benefits) on benefits to families or children. On average, each child received benefits worth 3,314 Euro, while 67 percent (64.8 percent periodic plus 2.2 percent lump-sum) were cash payments (Eurostat, 2018). The German government spent 35.9 billion Euros on child benefits in 2017 (Statistisches Bundesamt, 2018a). In 2017, the average woman in Germany had 1.6 children (Statistisches Bundesamt, 2018b) and the average monthly net salary was 1,888 Euro. If child benefits for 1.6 children (192 Euro for the first and second child in 2017, 307.2 for 1.6 children, Bundesagentur für Arbeit 2018) were simply added on top of the average monthly net salary, this would correspond to 14 percent of net income.

affect voting preferences and the demand for redistribution (Luttens and Valfort, 2012). This chapter presents one framework that, just as shown in the application, could be used to study questions like the ones asked above. There is still research to be done, both theoretical and empirical, to better understand violations of fungibility and to be able to thoroughly predict behavioural effects of policies.

Chapter II.

Empirical Applications

II.1. Ignoring Millions of Euros: Transfer Fees and Sunk Costs in Professional Football

II.1.1. Introduction

According to neoclassical economics, decisions should be based exclusively on an action's marginal costs and benefits. Being irreversible, sunk costs should not be taken into account when evaluating available alternatives. However, personal experience teaches us that we often behave differently if we have already invested time, money or effort in a project. Since the first studies on the sunk-cost fallacy (Thaler, 1980; Arkes and Blumer, 1985) this behaviour has been studied in many economic and psychological experiments. Yet it is often argued that experimental results lack generalizability and only consider hypothetical or low-stakes decisions. Despite these weaknesses, evidence of the sunk-cost fallacy outside the laboratory is rather scarce (Keefer, 2017).[1] Highly sensitive data is necessary to detect the sunk-cost fallacy for both corporate and individual behaviour. Of course, this data is difficult to obtain. With abundant data in the context of professional sports, economists have discovered a unique opportunity to analyse the sunk-cost fallacy and other phenomena (Kahn, 2000). However, studies so far have exclusively examined the sunk-cost fallacy (or

[1] Augenblick (2015) and Ho et al. (2018) are exceptions for empirical and non-sports related studies.

escalation of commitment[2]) in professional sports leagues' draft systems[3], where a rookie's salary is determined by his draft order. The articles examine whether a player's draft order and his corresponding salary affect his subsequent utilisation by the club to which he was drafted.

Importantly, in most leagues that apply a draft system, a large proportion of the salary costs are paid out biweekly or monthly during the season (e.g. Keefer, 2015). At the same time, the coach can continuously observe a player's performance and decide whether to employ him. It can therefore be argued that the labour costs are not experienced as sunk. Apart from that, parts of the salary are paid in the form of merit-based bonuses. This turns a fraction of a player's salary into marginal rather than sunk costs.

Unlike the draft system, teams in European football leagues have three different options to acquire their players. First, teams can train young players to a professional level. Second, they can sign players whose contracts expire or who are currently without an employer and therefore free of charge. Third, teams can compensate competing teams to sign one of their players with an ongoing contract. In the latter case, transfer fees are paid. With Neymar da Silva Santos Júnior's move from Futbol Club Barcelona to Paris Saint-Germain Football Club for 222 million Euros, these fees have risen to incredible levels. Although Neymar's transfer and its fee is unique to date, it typifies the overall trend in the market. By June 2018, the five most expensive transfers in history took place between 2016 and 2018. As Figure II.1 demonstrates, this development is also apparent in the German Bundesliga, with the average transfer fee having more than doubled from 2012 to 2016. Due to the strong contrast between free and fee-bound transfers, such a system is expected to be susceptible to the sunk-cost fallacy.[4] I therefore hypothesise that there is a sunk-cost effect in professional football, where players are mostly exchanged on a transfer market. For that reason, I investigate whether player utilisation in German professional

[2]The terminology "escalation of commitment" more generally refers to the phenomenon that decision makers exaggerate investments following previous commitment. The sunk-cost fallacy is associated with commitment following previous expenditures of economic resources (Camerer and Weber, 1999, p. 60).

[3]In a draft, teams alternately select rookies from a pool of young talented players.

[4]The context is comparable to the market for yearlings described by Camerer and Weber (1999, p. 81), in which young unraced horses are bought for relatively large amounts of money, but dropped if they perform poorly in their debut.

football is affected by initially paid fees. More specifically, I analyse the highest league in Germany, the Bundesliga.

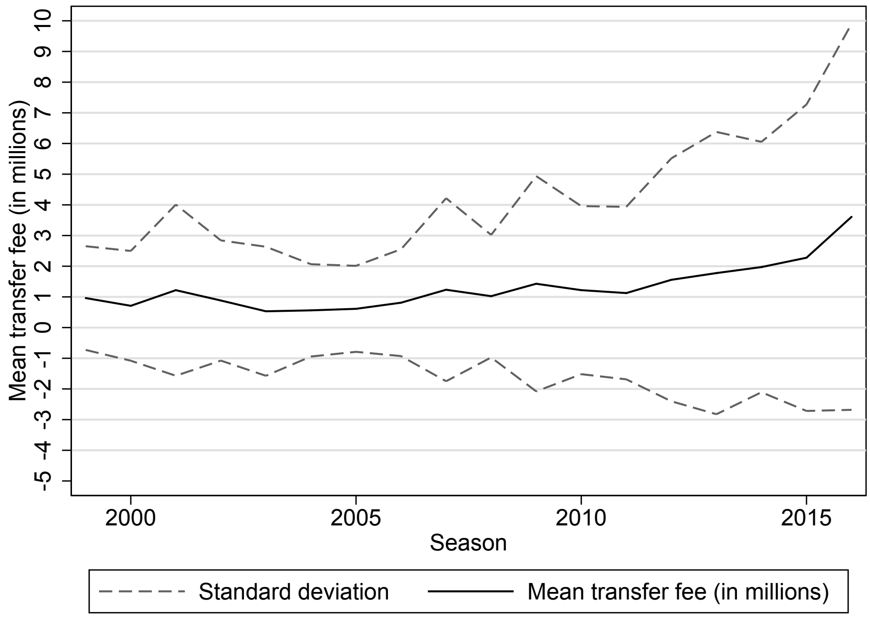


Figure II.1.: Mean transfer fee in the German Bundesliga from 1999/2000 until 2016/2017.

I am hereby able to contribute to the literature in multiple ways. To my knowledge, this is the first study that examines the sunk-cost fallacy in European sports in general and professional football in particular. So far, existing studies in the sports environment have used data from American football, basketball, and baseball in the United States and Australian football in Australia. The European setting allows a study of the sunk-cost fallacy in another labour market with different rules. There is neither a draft system nor a salary cap in European professional football. Instead, players are traded for money. Supply and demand determine transfer fees and salaries. The football labour market is therefore more similar to common labour markets than its US counterpart. Moreover, I control for two variables that are often argued to confound the results, which have not yet been accounted for. First, by including Google hits of players, I control for fan appeal. Second, coaches might be more likely to consider transfer fees in their line-up decision with players who were acquired during the coach's own spell (Staw, 1976; Pedace and

Smith, 2013). I do not find evidence for an effect of either of these. Finally, in addition to the seasonal level, I conduct the analysis on the level of individual matches, obtaining a sample size many times larger than that of comparable studies.

In contrast to the majority of previous articles (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995) that studied the sunk-cost fallacy in the context of professional sports, I am not able to find evidence supporting this behavioural bias on a seasonal level. An analogous analysis on the match level reveals a sunk-cost effect. However, the corresponding coefficient is negligible when compared to those of measures of performance and decreases with a player's tenure. Hence, the overall results corroborate rational professional sports team management. This is in line with the findings of Borland et al. (2011) and Leeds et al. (2015). Playing time in the German Bundesliga is primarily determined by previous and predicted performance. Coaches and managers therefore seem to be able to ignore the huge transfer fees they paid in the first place.

I proceed as follows: Section II.1.2 summarises the relevant literature. I then describe the data in Section II.1.3 and the empirical approach in Section II.1.4. Section II.1.5 presents and discusses the results. Section II.1.6 concludes.

II.1.2. Literature

One of the earliest studies on evidence of sunk-cost effects is a set of experiments by Arkes and Blumer (1985). In a field experiment, the authors randomly provided discounts to some purchasers of a subscription to a theatre series. Subsequently, they recorded how many plays the subjects attended. As the discounts were assigned randomly, preferences over the plays and hence the number of plays attended should, on average, not differ between treatment groups. However, the group that paid the normal price attended significantly more plays than subjects who received a discount. Arkes and Blumer (1985) therefore conclude that, in this example, subjects took sunk costs into account, which provides evidence of the sunk-cost fallacy.

Following a series of other experiments on the sunk-cost effect and the phenomenon of escalation of commitment (see Friedman et al., 2007 and McAfee et al., 2010 for surveys), one of the first and most prominent field studies on the sunk-cost fallacy is Staw and Hoang (1995). The authors use the National Basketball Association (NBA) draft between 1980 and 1986 to test whether a player's time on the pitch and survival in the NBA depend on the financial commitment incurred by the draft order of a player. In a draft, experts first rank college players (rookies) by talent. Starting with the lowest ranked team of the past season, each team then alternately selects one young prospect from the pool of rookies. The order of the draft determines the rookie's salary. The higher a rookie's position in the draft, the sooner he will be selected, and the higher is his salary. Since these salary costs, as well as the opportunity costs of having neglected the option to choose another player, are determined at the start of a given season, they can be considered sunk. Consequently, the managerial decision on who to send onto the pitch should only be based on player productivity. Yet Staw and Hoang (1995) find significant effects of draft order on players' playing time and survival in the NBA. An earlier draft and the correlated higher salary granted the player more time on the pitch and a longer career in the NBA after controlling for productivity and other factors.

Camerer and Weber (1999) attempted to challenge the results of Staw and Hoang (1995) by re-examining a sample of NBA players in the 1986 to 1991 drafts. They tested the presence of sunk-cost effects, but accounted for several other alternative rational explanations. For this purpose, Camerer and Weber (1999) used a different set of control variables (e.g. disaggregated measures of performance) and added the quality of back-up players, pre-draft player rankings by an outside expert, and control for players being traded. After the inclusion of these additional variables, they apply a two-stage regression model, intending to extract the informational content that the draft order has on performance. Nevertheless, Camerer and Weber (1999) find persisting evidence of a sunk-cost effect, albeit to a slightly smaller extent.

Based on these findings for the NBA and the characteristics of the European football transfer market as described in Section II.1.1, I formulate the main hypothesis of this study:

Hypothesis 1. *Professional football managers in the Bundesliga exhibit the sunk-cost fallacy by considering paid transfer fees in addition to predicted performance when fielding players.*

In their article, Camerer and Weber (1999) elaborate on rational explanations for occurrences of sunk-cost effects. First, uncertainty about the costs and benefits of an action promote the escalation of the very action. With regard to football players, this is less of a concern. The transfer fee paid by the team to acquire the player is known to the team executives and modern technologies allow the precise measurement of performance. This also precludes a self-serving bias in judging costs and benefits (Camerer and Weber, 1999, p. 61). Second, the interests of a team coach and those of the team, its owners and its fans could be non-aligned. Transfers in German professional football are usually a joint decision taken by the coach and the entire management, including scouts as well as athletic and finance directors. Furthermore, it is unlikely that team coaches pursue a different goal to that of long-term stakeholders. It can be assumed that both strive to maximise playing success (Garcia-del Barrio and Szymanski, 2009).

Finally, Camerer and Weber (1999) suspect that teams might try to recoup the sunk costs by investing further playing time for a given player. While the authors argue that this is not an issue in the NBA, it might indeed be one in both Bundesliga and NBA. Since players in professional football are frequently traded, teams in principle have the opportunity to recoup a fraction or even more of the initially paid transfer fee. To this end, players must perform well to attract potential buyers and to generate a higher transfer price. Additional time on the pitch for a player that is planned for sale might increase the perceived ability of a given player. Therefore, if coaches arrive at the decision to sell a player but still think he is undervalued, they might decide to grant him more playing time. However, ex ante, it is unclear whether a player can perform well enough to increase his market value. Hence, fielding him is risky. Note that these considerations apply to all players. Thus, irrespective of whether or not a player is up for sale, managers should only invest additional playing time in the player if they think it can increase his value. Consequently, even managers who seek to recoup transfer fees should ignore initially paid transfer fees and only focus on a player's potential. Yet this explanation still leaves the possibility of erroneously identifying a sunk-cost effect. Given that additional playing time promotes player performance, it can be worthwhile for managers to field players they expect to improve, even if this is not justified by the currently predicted performance.[5] Accordingly, I investigate the following hypotheses:

Hypothesis 2a. *More playing time leads to a higher performance of a player.*

Hypothesis 2b. *Managers invest in players by granting them more playing time.*

Apart from Staw and Hoang (1995) and Camerer and Weber (1999), there are four other studies that investigate the sunk-cost effects of draft order on playing time. Borland et al. (2011) examine draft order effects in the Australian Football League (AFL). Using the amount of games played as dependent variable and accounting for the information contained in a player's draft order, they find no evidence of a sunk-cost effect. Instead, Borland et al. (2011) find that coaches grant more playing time to promising talents, expecting the additional experience to improve their performance, and thus supporting Hypothesis 2b.

Consistent results are provided by Leeds et al. (2015) for the NBA. Although the initial results indicate that the draft order has an effect on playing time, a regression discontinuity design eliminates this effect. In order to control for unobserved variables, Leeds et al. (2015) exploit the discontinuity between the first and the second draft round. Moreover, the authors control for injuries and suspensions by limiting the dependent variable to the net potential playing time. While I am also able to control for injuries and suspension spells, my data does not allow a regression discontinuity design.

Similarly, Keefer (2017) uses the discontinuity between the first and the second round in the National Football League (NFL) draft to control for unobserved variables, applying a fuzzy regression discontinuity design. In contrast to Leeds et al. (2015), the author finds that players drafted in the first round receive a wage premium. The additional earnings result in more playing time. Keefer (2015) substantiates these results.

[5] As NBA players can also be exchanged for draft positions or other players, the same issue might arise there as well.

In addition to these studies, further scholars considered draft order effects in studies with a different focus. Groothuis and Hill (2004) find evidence that being drafted earlier is associated with a longer career. Similarly, results obtained by Coates and Oguntimein (2010) suggest that draft order has an effect on playing time and career length. Interestingly, research by Pedace and Smith (2013) supports the idea that managers overly invest in players recruited by themselves. They find that successors are more likely to divest poorly performing players.

II.1.3. Data

For the analysis, I use data from the highest professional football league in Germany, the Bundesliga, and primarily obtain data from two websites, `www.transfermarkt.de` and `www.kicker.de`. I use DataGorri[6] for the data collection, a tool that automates the collection of tabular data such as performance tables and rankings. Transfermarkt is a popular German-based football information website where community members track transfer fees and successfully discuss market values (Herm et al., 2014; Peeters, 2018). The transfer fees that are paid constitute my measure of sunk costs. The market value is an estimation of a player's value to a team.

Additionally, the website provides match-level and season-level data on measures of performance (number of goals, assists, cards, appointments to the roster, minutes played and matches, substitutions as well as the team's average amount of points won when a given player has played[7]) and characteristics of players (age, nationality, footedness, height, position, tenure). In existing studies on the sunk-cost fallacy, all observations are of young rookies. In contrast, players of all ages can be sold and purchased on the European football transfer market. Therefore, I control for the effect age has on playing time. Analogous to Leeds et al. (2015) and Keefer (2017), I account for native players playing less or more often than foreign ones by including a dummy for German citizenship.

[6]See Appendix C for the corresponding article "DataGorri: A Tool for Automated Data Collection of Tabular Web Content" published in *Netnomics*, 2018, Volume 19, Issue 1-2, p. 31-41. Please see `https://doi.org/10.1007/s11066-018-9125-2`.

[7]In modern European football, teams earn zero points for a defeat, one point for a draw, and three points for a win.

Transfermarkt also features information on coaches. During his spell, a coach is often involved in transfer decisions. The corresponding transfer fees might carry more weight in his line-up decisions (Staw, 1976; Pedace and Smith, 2013; Keefer, 2015). Moreover, I conjecture that a potential significant sunk-cost effect might vary with respect to a coach's experience. Therefore, I collect and add corresponding variables and, where appropriate, interaction terms to the estimations.

I also use Transfermarkt to record whether a player is on loan. Besides final player transfers, European football teams have the opportunity to lend and borrow players, usually for 6 months to two seasons. This means that while players on loan remain under contract with the lending team, they are an inherent part of the borrowing team's roster and are not allowed to play for the lending team. These players are often expected to have a high potential, which managers may want to test prior to a final transfer. Also, more competitive teams often lend young talented players to lower ranked teams to provide these players with more playing time and opportunities to develop and prove themselves. Otherwise, a loan can be an emergency replacement for an injured or suspended player that is only needed until the absent player returns. Generally, teams can borrow players to increase overall team size and/or quality in the short term. Just like final transfers, teams can lend a player entirely for free or for a loan fee[8] (which I treat as a transfer fee).[9] In the sample, five percent of the observations are for players on loan.

Transfermarkt also registers spells of injuries and suspensions of players. I use these to calculate the maximum amount of time a player could potentially spend on the pitch. Since reliable data on injury and suspension spells is only available from the 2007/2008 season onwards, I restrict the sample to the 2007/2008 to 2016/2017 seasons. I still resort to values from earlier seasons for lagged variables other than those related to injuries and suspensions.

Finally, apart from rankings, Transfermarkt provides information as to whether teams played international competitions like the UEFA Champions League (CL) or the UEFA

[8]Although many teams have to pay a fee for players on loan, the contract is referred to as a loan and not a rental contract.

[9]As a special case with loans, the salary costs are often split between the lending and the borrowing team.

Europa League (EL) during given seasons. Participation implies a more intense playing schedule and is likely to affect individual players' playing time in the national league. Coaches might want to give certain players a break, which can result in more or less playing time on the individual player level. For that reason, I include dummy variables for teams that played international matches. In addition, I repeat the analysis only with teams that did not play internationally.

At the sports newspaper Kicker, a team of expert journalists evaluates players' performances after every Bundesliga match. They assign grades on a scale from one to six, with one being the best score. I use the grades per match and the average grades per season as an aggregated measure of performance.

Both Staw and Hoang (1995) and Camerer and Weber (1999) argue that fan appeal could be a critical confounding factor when analysing the effect of sunk costs on playing time. Usually, popular players are more valuable to teams as they generate higher jersey sales and attract more spectators to the stadium. Hence, regardless of their performance, it could make economic sense to grant more playing time to more expensive players. I am not aware of any study that uses sports data in the context of the sunk-cost fallacy that could control for fan appeal. To account for popularity, I collect the number of Google hits per season for each player by searching for "(player name) (team name) (fussball[10])".[11] To record only the Google hits for a given season t, I restrict the Google hits using Google Tools to between the start (July 1 of year t) and the end (June 30 of year $t+1$) of that season.[12] Thus, for a player X who played in the German Bundesliga from the 2008/2009 until the 2012/2013 season, I obtain a specific number of Google hits for each of the five seasons.

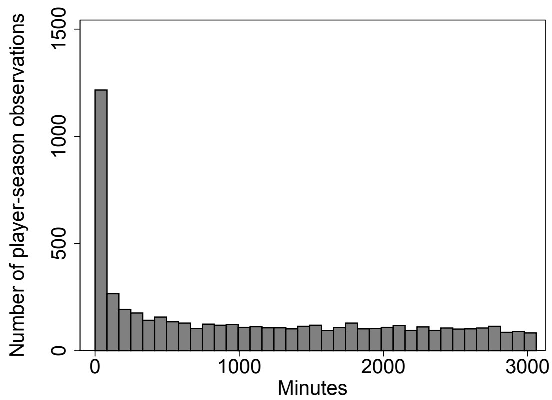
Table II.1 summarises the statistics on players. Each observation hereby represents one player in the case of personal characteristics (e.g. nationality). In other cases it represents one transfer, one match, or one season per player. Hence, each player usually comprises

[10] "Fussball" is the German word for football and was included in the search request to restrict the query to results related to football.

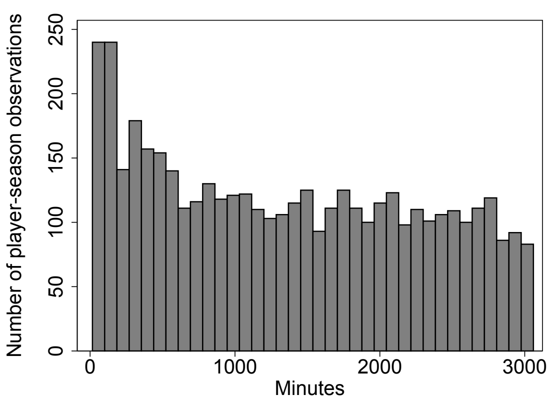
[11] The results of players who moved from one Bundesliga club to another in a given season were added together to obtain one single figure per player and season.

[12] The Python code to download that data can be obtained from the author on request.

more than one observation. The average player in the sample is about 24 years old. Interestingly, players initially appear to be valued higher on average by the Transfermarkt community (3.51 million) than what teams actually paid as transfer fees (1.72 million). Across the sample that starts with observations in 2007, a time where the Internet was not yet as common as it is now, players have an average of about one thousand Google hits per season. Playing time for the average player is a little less than half a season. As Figure II.2a demonstrates, a large fraction of players does not play at all. However, these observations mostly relate to talented young players from youth teams who were appointed to a team's roster as back-ups but were not given a chance to prove themselves. If a player does not play a minimum amount of minutes (usually thirty minutes per match), he is not graded by Kicker. Without a measure of performance, these players drop out of the corresponding estimations. I resort to other measures for robustness checks (points per minute and a disaggregated measure of performance). Figure II.2b shows the distribution of playing time per season for graded players only.



(a) All players.



(b) Players evaluated by Kicker.

Figure II.2.: Histograms of playing time per season per player.

II.1.4. Empirical method

In line with existing studies on the sunk-cost fallacy in professional sports, I regress a measure of the player's time on the pitch on the sunk cost his current team has incurred. The latter corresponds to the transfer fee paid to acquire the player in the first place.

Table II.1.: Summary statistics.

	Mean	Std. Dev.	Min	Max	Obs.
Grade	3.74	0.54	2.00	6.00	4,352
Matches	15.53	11.51	0.00	34.00	5,390
Minutes	1,112.30	978.40	0.00	3,060.00	5,390
Fraction of minutes played	0.45	0.37	0.00	1.00	5,390
Substitutions (in)	3.14	3.89	0.00	27.00	5,390
Substitutions (out)	3.15	4.03	0.00	29.00	5,390
Goals	1.59	3.18	0.00	31.00	5,390
Assists	1.41	2.38	0.00	22.00	5,390
Points per match	1.16	0.73	0.00	3.00	5,390
Yellow cards	2.03	2.41	0.00	14.00	5,390
Red cards	0.05	0.22	0.00	2.00	5,390
Market value (in millions)	3.51	5.78	0.00	75.00	5,390
Loan	0.05	0.21	0.00	1.00	5,390
Google hits (in thousand)	0.93	2.68	0.00	48.60	5,390
Age	24.40	4.39	16.00	44.00	5,390
Minutes per match	38.23	41.50	0.00	90.00	158,180
Goals per match	0.10	0.34	0.00	5.00	84,498
Assists per match	0.09	0.32	0.00	4.00	84,498
Yellow cards per match	0.13	0.34	0.00	1.00	84,498
Red cards per match	0.00	0.06	0.00	1.00	84,498
Match grade	3.59	0.96	1.00	6.00	70,908
Transfer fee (in millions)	1.72	4.04	0.00	43.00	1,945
Height	1.83	0.06	1.65	2.01	1,868
Right foot	0.59	0.49	0.00	1.00	1,995
Left foot	0.20	0.40	0.00	1.00	1,995
Both feet	0.14	0.34	0.00	1.00	1,995
German (1=German)	0.45	0.50	0.00	1.00	1,995
Home score	1.63	1.35	0.00	9.00	3,060
Away score	1.25	1.19	0.00	8.00	3,060

Note: Each player or each season/match/transfer of each player counts as one observation.

With respect to control variables, I attempt to stay as close to the studies on the sunk-cost effect in US sports leagues as the different setting allows, while adding additional variables where needed. So far, studies have only investigated the sunk-cost effect on the seasonal level. However, the performance in previous matches is more likely to matter for the line-up decisions than entire previous seasons. As Transfermarkt and Kicker also provide match-level data, I investigate the sunk-cost effect on both a seasonal and match level.

Transfer fees, predicted performance, and playing time at seasonal level

Regarding the dependent variable in the season-level analysis, I follow the approaches of Staw and Hoang (1995) and Camerer and Weber (1999), and Leeds et al. (2015). The two former apply Ordinary Least Squares (OLS) to regress the playing time per season on the sunk costs and control for performance as well as injuries that reduce the minutes players potentially could play. Leeds et al. (2015) take a different approach, incorporating injuries and suspensions into the dependent variable. In the same way, I use the ratio of actually played minutes out of a player's total potential. In order to calculate the potential playing time, I take the maximum playing time per season of 34 matches (17 matches for transfers in the winter transfer window) and subtract matches the player missed due to injury or suspension (disciplinary sanctions due to five yellow cards, yellow-red cards, red cards, or team-internal suspensions), and missed matches due to individual days off or appointments to the national team. The sample contains both players who have played all and those who have played none of their potential matches.

Due to the characteristics of the transfer market, transfers can be categorised into free and fee-bound transfers. For that reason, I include two variables for transfer fees. To analyse the extensive margin, I introduce a dummy as to whether a transfer incurred a fee or not. If yes, the transfer fee paid constitutes the intensive margin.

Similar to Staw and Hoang (1995), I use Kicker grades as an aggregated measure of performance to control for player quality. Further, I control for market values at the beginning of each season. These are exogenous on the first match day and explain variance that cannot be explained by the Kicker grades. They are continuously updated and can serve as additional proxies for player potential. Missing market values usually result from the respective players being unknown and of very low value.[13] For that reason, I set the missing market values to zero.

Just like Camerer and Weber (1999), I include the performance of back-up players (grades, points per match, or disaggregated measures) as a control variable. The quality of all of the other players in the team who could potentially replace the player in focus also impacts his playing time. For this, I categorise all players as either goalkeeper, defender, midfield, or attack and calculate the average performance (e.g. grades) of the other players who play in the same position. This automatically eliminates all observations of goalkeepers who played every match in one season, as no back-up performance for substitutes exists. In these situations, I cannot be sure whether the goalkeepers played all the matches due to their ability or due to a lack of alternatives. Additionally, I also use the positional variable in order to control for effects related to a player's position.

Furthermore, the overall strength of a team might play a role. Its effect on playing time could go in either direction. On the one hand, better performing teams have higher earnings (DFL Deutsche Fußball Liga GmbH, 2017) and would therefore be able to hire more players for the subsequent season. Larger rosters could result in less playing time per player. Alternatively, successful teams could use the larger budget to replace players with better and more expensive ones. If the number of players in a team thereby remains constant, the performance of previous seasons should not alter the average player's time on the field. On the other hand, one could expect teams that performed poorly to buy additional players or higher quality replacements if their budget allows. To control for such effects, I include the previous season's final rank per team (as in Keefer, 2017) and the total number of players in a team. Finally, I control for season and team effects.

[13] Starting from 2005, one can find meaningful market values for almost all players in the German Bundesliga on Transfermarkt.

In the first estimation, I use OLS to regress playing times on the pitch on transfer fees, including lagged performances as well as player and team controls.

$$
\begin{aligned}
Minutes_{i,t} = {} & \beta_0 + \beta_1 Grade_{i,t-1} + \beta_2 BackupGrade_{i,t-1} + \\
& + \beta_3 FeeBound_{i,t} + \beta_4 TransferFee_{i,t} + \\
& + \beta_5 Loan_{i,t} + \beta_6 MarketValue_{i,t} + \\
& + \beta_7 Injured_{i,t} + \beta_8 Suspended_{i,t} + \\
& + \beta_9 MatchesOtherTeam_{i,t} + \beta_{10} Winter_{i,t} + \\
& + \beta_{11} Age_{i,t} + \beta_{12} AgeSquared_{i,t} + \beta_{13} German_i + \beta_{14} Google_{i,t-1} + \\
& + \beta_{15} \#PlayersTeam_{i,t} + \beta_{16} CL_{i,t} + \beta_{17} EL_{i,t} + \beta_{18} Rank_{i,t-1} + \\
& + \textstyle\sum_{j=19}^{21} \beta_j Position_{j,i} + \sum_{k=22}^{52} \beta_k Team_{k,i,t} + \sum_{l=53}^{61} \beta_l Season_{l,t}
\end{aligned}
\tag{II.1}
$$

The second estimation employs playing time as a fraction of total potential playing time. The dependent variable is therefore bound between 0 and 1. As Figure II.3 shows, many players play none or all of their potential minutes. Given their past performance, an OLS estimation would predict that some of them play less than zero minutes or more than their potential maximum. Yet I only observe a fraction of minutes played of zero to a hundred percent. For that reason, I chose a Tobit model as the main identification method.

As first suggested by Camerer and Weber (1999), I precede the main estimation with a linear regression predicting current performance using lagged performances, transfer fees, and controls. This disentangles the information a transfer fee contains regarding performance and its effect on playing time. Hence, the final empirical strategy is a two-stage model with a linear regression predicting the performance of a player (his Kicker grade, average points per match, or goals, assists, and cards) and a Tobit regression with the fraction of minutes played out of the potential playing time as the dependent variable. I follow the example of Staw and Hoang (1995) and Camerer and Weber (1999) and estimate the model for each season a player was under contract with the same team. Since I use lagged grades, I lose the observations from the first season for players who moved up from non-graded (non-domestic or lower level) leagues. The estimation for the first season is only based on 65 observations with no significant coefficients and I report only seasons

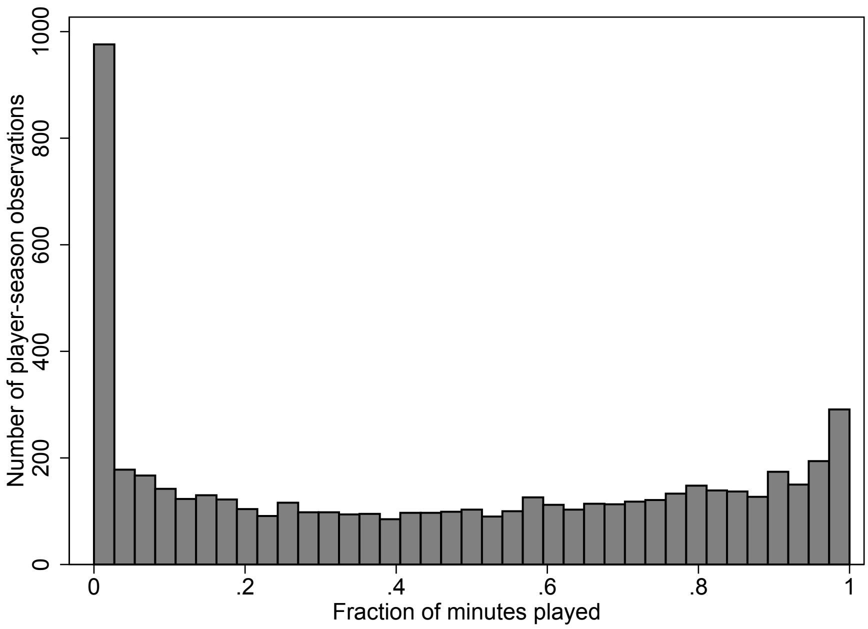


Figure II.3.: Histogram of the fractions of playing time out of the total potential playing time per season per player.

two to five. However, in general, I can resort to Kicker grades prior to the 2007/2008 season.

The model can be written as

$$FractionMinutes_i^* = \widehat{Performance}_i\beta + X_i\gamma + u_i \tag{II.2}$$

$$\widehat{Performance}_i = \sum_{j=1}^{4} Performance_{t-j,i}\Pi_j + X_i\Phi + v_i, \tag{II.3}$$

where the fraction of minutes played is the unobserved latent variable. The observed dependent variable is equal to

$$FractionMinutes_{1i} = \begin{cases} 0, & \text{if } FractionMinutes_i^* < 0 \\ FractionMinutes_i^*, & \text{if } 0 \leq FractionMinutes_i^* \leq 1 \\ 1, & \text{if } FractionMinutes_i^* > 1. \end{cases} \tag{II.4}$$

X represents the matrix of regressors, β, γ, Π_1 through Π_4, Φ the parameters to be estimated and u_i and v_i the random error terms. The main equation to be estimated using a Tobit model (Equation (2)) is

$$\begin{aligned} FractionMinutes_{i,t} = {} & \beta_0 + \beta_1 \widehat{Performance}_{i,t} + \beta_2 BackupPerformance_{i,t-1} + \\ & + \beta_3 FeeBound_{i,t} + \beta_4 TransferFee_{i,t} + \\ & + \beta_5 Loan_{i,t} + \beta_6 MarketValue_{i,t} + \\ & + \beta_7 Age_{i,t} + \beta_8 AgeSquared_{i,t} + \\ & + \beta_9 German_i + \beta_{10} Google_{i,t-1} + \\ & + \beta_{11} CL_{i,t} + \beta_{12} EL_{i,t} + \beta_{13} Rank_{i,t-1} + \\ & + \textstyle\sum_{j=14}^{16} \beta_j Position_{j,i} + \sum_{k=17}^{48} \beta_k Team_{k,i,t} + \\ & + \textstyle\sum_{l=49}^{57} \beta_l Season_{l,t}. \end{aligned} \tag{II.5}$$

In the first specification of the Tobit estimation, I use Kicker grades as measure of performance. Further, I resort to the average points per match as an aggregated measure of performance and goals, assists, and penalty cards as a disaggregated measure of performance.

Transfer fees, predicted performance, and playing time at match level

On the aggregate seasonal level, many confounds cancel each other out (e.g. each team is both the home team and the away team in the two meetings per season). Other factors have to be taken into account on a match level. One might employ a different line-up and substitution strategy against directly competing teams than teams at the other end of the ranking. Additionally, I conjecture that the match day might matter. At the beginning of each season, coaches could test several players. On the other hand, injuries or an intense competition at the end of a season could alter playing time on later match days. Therefore, I drop the variable indicating the team's final rank in the previous season and add the teams' difference in rank at kickoff, the match day as well as corresponding squared terms to the set of control variables of Models II.1 and II.5. A player's tenure with his current team measured in matches is also added. Furthermore, I account for players who are instructed by the same coach who hired them.

I also eliminate the variables that account for the number of matches a player was injured, suspended, or played with another team from Model II.1. In these cases, the player plays zero minutes and it is not up to the coach to decide how many minutes he fields this player. Instead, I only estimate the match level model for players who are available.

II.1.5. Results

Transfer fees, predicted performance, and playing time at seasonal level

Main analysis The OLS regression at a seasonal level (Table II.2) demonstrates that managers in the German Bundesliga do not appear to be very susceptible to the sunk-cost fallacy. Only the variable of the intensive margin of transfer fees in the second season is significant. Yet the coefficient is negative, contrary to a sunk-cost effect. Otherwise, as hypothesised, past performances of the player himself and those of his teammates on the same position predict playing time well. Alongside measures that control for players being unavailable due to injury, suspension, or appearances for the national team, or a transfer in the winter transfer period, the assessment of the Transfermarkt community at the beginning of the season is significant in all of the four seasons that were covered. In contrast, the popularity of a player, as measured in Google hits, has no additional influence on a player's time on the pitch. Notably, according to the OLS estimates, German players play significantly more minutes in two of the four seasons.

In the first stage of the IV Tobit model (Table II.3) it is clear that the performance in the previous season is the best predictor of current performance. The grade from two years before a given season has some explanatory power for a current season. The grade from three years before does not matter anymore. Since players are evolving, this is not very surprising. Remarkably, the transfer fee does not predict future performance very well. Having moved to a team for a transfer fee is associated with a slightly better grade. However, this effect is only significant in the second season. Thus, it cannot be argued

Table II.2.: Ordinary Least Squares regression.

	Minutes played			
	Season 2	Season 3	Season 4	Season 5
Grade_{t-1}	-455.4***	-586.6***	-490.6**	-583.1***
	(66.42)	(84.68)	(137.4)	(134.4)
Back-up grade_{t-1}	529.1***	307.0**	701.6***	365.3
	(112.5)	(97.90)	(169.5)	(278.3)
Fee-bound transfer	83.06	-4.832	-35.56	72.56
	(43.77)	(81.46)	(93.65)	(139.3)
Transfer fee (in millions)	-27.04*	-12.10	-0.948	6.841
	(11.58)	(11.61)	(10.78)	(8.732)
Loan	-19.57			
	(130.3)			
Market value (in millions)	57.21**	33.01**	34.49**	26.22**
	(18.26)	(9.913)	(10.92)	(9.081)
Injured matches	-54.43***	-54.98***	-69.55***	-79.14***
	(3.499)	(5.158)	(4.262)	(5.965)
Suspended matches	179.8***	139.6	44.27	42.95
	(30.61)	(74.95)	(31.00)	(53.00)
Matches with other team	-73.61***	-128.8***	-149.2***	-222.1***
	(7.785)	(20.63)	(19.69)	(37.55)
Winter transfer	-1046.6***	-1007.0***	-1160.5***	-1209.3***
	(53.05)	(102.0)	(144.0)	(184.6)
Age	45.33	-67.93	-52.41	-142.3
	(56.27)	(102.0)	(157.0)	(139.6)
Age squared	-0.886	0.934	1.080	2.540
	(1.114)	(2.018)	(2.964)	(2.553)
German (1=German)	129.1*	35.59	229.3*	180.7
	(46.68)	(81.63)	(101.9)	(101.0)
Google hits_{t-1} (in thousands)	30.45	-26.65	19.69	-45.22
	(21.35)	(18.10)	(35.73)	(44.62)
Number of players in team	11.18	-17.22	1.295	15.80
	(6.037)	(12.04)	(17.68)	(15.18)
Champions League	-99.82	-8.251	-262.8	-67.81
	(193.8)	(155.1)	(205.2)	(242.5)
Europa League	18.58	129.3	-104.8	-28.84
	(116.4)	(118.5)	(144.1)	(119.5)
Rank_{t-1}	-8.180	9.406	-50.01*	1.847
	(12.86)	(12.52)	(21.31)	(24.51)
Constant	-403.8	4640.8**	1890.7	3959.7
	(761.8)	(1635.4)	(2771.0)	(2460.7)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.513	0.449	0.531	0.517
Observations	869	590	356	242

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that transfer fees serve as a long-term indicator of performance. Instead, the continuously updated measure of market value is correlated with a better performance in three of the four seasons. Again, German players on average receive better grades in their second season. However, since the effect is not present in either of the other seasons, Kicker evaluations do not seem to exhibit a discriminatory bias.

The second-stage Tobit regression (Table II.4) confirms the results from the OLS regression. Line-up decisions are primarily driven by predicted performance. Apart from the fourth season, both variables that relate to transfer fees are insignificant. In fact, a higher transfer fee is even associated with less playing time. Although other variables become significant in some seasons, only predicted performance constantly explains players' time on the pitch. In short, I cannot find that football coaches in Germany consider transfer fees when selecting players for the next match on a seasonal level.

Admittedly, it is possible that I am unable to find an effect because the sample size is too small. I therefore estimate effect sizes that I can preclude according to the data in a statistical power analysis. Since there is no straightforward method to conduct a power analysis following a two-stage Tobit estimation, I approximate a threshold for each of the four estimations in Table II.4 by using a power analysis for multivariate logistic regression designs with a continuous predictor variable (the transfer fee). I start by calculating the statistical power given the actual data. Subsequently, I increase the effect size (in the positive direction) in increments until I obtain a statistical power of 80 percent. By doing so, I can reject effect sizes greater than .012 in Season 2, .013 in Season 3, .016 in Season 4, and .017 in Season 5 with a probability of 80 percent. Assuming the effect size in Season 2 is .012 and ignoring the insignificant and negative effect of the extensive margin of transfer fees, an increase of one million Euro in the transfer fee would only result in a 1.2 percentage point increase in the fraction of played minutes. Given that the sample mean of transfer fees for players in their second season is 2.58 million, the average player plays 3 percentage points more than a player hired for free, or on average 58 instead of 55 percent of the potential minutes. On average, this equals 66 minutes more over a complete season, and therefore not even an entire match.

Table II.3.: First-stage linear regression predicting grades.

	Grade			
	Season 2	Season 3	Season 4	Season 5
Grade$_{t-1}$	0.209***	0.299***	0.277**	0.331*
	(0.0572)	(0.0420)	(0.0843)	(0.132)
Grade$_{t-2}$		0.148**	0.152**	0.0727
		(0.0553)	(0.0494)	(0.108)
Grade$_{t-3}$			0.0390	0.121
			(0.0715)	(0.1000)
Grade$_{t-4}$				-0.0553
				(0.0518)
Back-up grade$_{t-1}$	-0.0818	0.0305	-0.160	0.0427
	(0.0838)	(0.0773)	(0.103)	(0.165)
Fee-bound transfer	-0.0712*	0.0101	0.0205	0.0825
	(0.0305)	(0.0534)	(0.0587)	(0.131)
Transfer fee (in millions)	0.0118	0.000694	-0.00423	-0.0167**
	(0.00898)	(0.00694)	(0.00584)	(0.00519)
Loan	-0.0542			
	(0.0721)			
Market value (in millions)	-0.0265*	-0.0119*	-0.00653	-0.0136*
	(0.0122)	(0.00582)	(0.00503)	(0.00539)
Age	0.0266	0.111*	0.0439	-0.216
	(0.0598)	(0.0474)	(0.0788)	(0.136)
Age squared	-0.000552	-0.00223*	-0.000782	0.00368
	(0.00113)	(0.000916)	(0.00141)	(0.00240)
German (1=German)	-0.127***	-0.0542	-0.00286	-0.111
	(0.0262)	(0.0319)	(0.0403)	(0.0756)
Google hits$_{t-1}$ (in thousands)	-0.0123	-0.00726	-0.00485	0.0523*
	(0.0114)	(0.0217)	(0.0148)	(0.0251)
Champions League	-0.0732	0.0360	-0.316	0.174
	(0.0982)	(0.158)	(0.163)	(0.0902)
Europa League	-0.174**	-0.0967	-0.241*	-0.0622
	(0.0569)	(0.0741)	(0.0973)	(0.113)
Rank$_{t-1}$	-0.0124	-0.00990	-0.0122	-0.00741
	(0.00790)	(0.00937)	(0.0121)	(0.0136)
Constant	3.258***	0.0548	1.513	5.141*
	(0.913)	(0.726)	(1.342)	(2.332)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	767	449	234	130

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table II.4.: Second-stage Tobit regression.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.072***	-0.648***	-0.793***	-0.769*
	(0.245)	(0.141)	(0.189)	(0.314)
Back-up grade$_{t-1}$	0.0741	0.138*	0.174	0.0397
	(0.0885)	(0.0652)	(0.0959)	(0.162)
Fee-bound transfer	-0.0257	0.00890	0.0244	0.0641
	(0.0461)	(0.0302)	(0.0513)	(0.114)
Transfer fee (in millions)	0.00515	-0.00126	-0.0123***	-0.00710
	(0.00876)	(0.00426)	(0.00271)	(0.00830)
Loan	-0.0617			
	(0.0768)			
Market value (in millions)	-0.00628	0.00279	0.00662	-0.00545
	(0.0127)	(0.00477)	(0.00474)	(0.00874)
Age	0.0406	0.0235	0.133*	-0.0534
	(0.0626)	(0.0401)	(0.0619)	(0.132)
Age squared	-0.000769	-0.000637	-0.00253*	0.000834
	(0.00118)	(0.000805)	(0.00115)	(0.00220)
German (1=German)	-0.0994*	-0.0407	0.0214	-0.0273
	(0.0435)	(0.0244)	(0.0391)	(0.0813)
Google hits$_{t-1}$ (in thousands)	-0.00538	0.00202	0.00725	0.0311
	(0.0126)	(0.0129)	(0.0155)	(0.0360)
Champions League	-0.138	0.0735	-0.253*	0.102
	(0.0959)	(0.0881)	(0.128)	(0.133)
Europa League	-0.194**	-0.0120	-0.201**	-0.114
	(0.0633)	(0.0421)	(0.0751)	(0.0782)
Rank$_{t-1}$	-0.0140*	-0.00126	-0.0262*	-0.00411
	(0.00697)	(0.00570)	(0.0113)	(0.0118)
Constant	3.924***	1.804*	0.218	3.657
	(1.130)	(0.708)	(0.984)	(2.997)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	767	449	234	130

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .105$), all Wald tests of exogeneity of the instrumented variable (predicted grade) are significant.

Furthermore, comparing the effect and sample sizes in this study and others demonstrates that the sunk-cost effect is at most relatively small in professional football. For example, Staw and Hoang (1995) and Camerer and Weber (1999) find a significant sunk-cost effect, but analyse substantially fewer observations in the first three seasons. For instance, while I use 767 observations in Season 2, Staw and Hoang (1995) use 241 and Camerer and Weber (1999) only use 202 observations.[14]

Finally, I test the hypothesis that teams might use playing time as an investment to promote players. Indeed, average transfer fees increase with age as long as players are 25 years old or younger and decrease thereafter (see Figure II.4). This suggests that players are still improving in the first half of their career. This development could be strengthened by providing young players with more playing time. It might be worthwhile fielding them regardless of their past performances. Therefore, I first analyse whether playing time

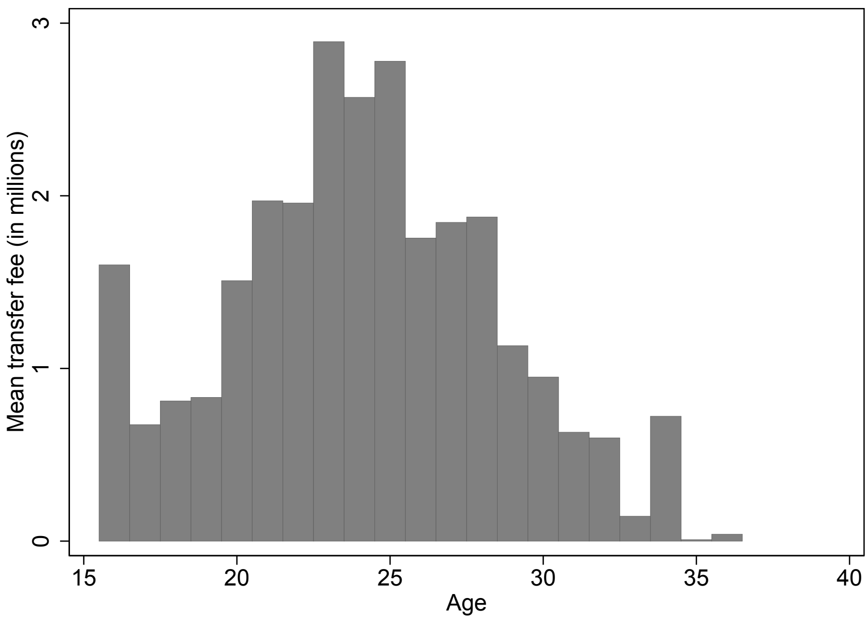


Figure II.4.: Mean transfer fee and player age in the German Bundesliga from 1999/2000 until 2016/2017.

can be considered an investment in young prospects by including an interaction term of

[14] Borland et al. (2011) have slightly more observations (e.g. 985 observations in Season 2), but also conclude that the sunk-cost effect found in their data disappears when taking into account the information contained in a player's draft order as well as incentives to award playing time to talented players.

past playing time and age when predicting grades. The results suggest that it benefits players of all ages to spend time on the pitch, supporting Hypothesis 2a (Table B.1). Having played a larger fraction of one's potential minutes in season $t-1$ is significantly associated with better grades in season t. The additional interaction terms of the young player dummy (younger than 22, 24, 26, and 28) and a player's past season playing time are insignificant. However, the changing sign from Specification (1) to (2) seems to be suggestive evidence that playing time is particularly effective to improve the performance in the subsequent year for players younger than 22 (Figure II.5). Moreover, I divide the sample into young and old players to see whether there are any significant differences in coefficients when estimating Model II.5. The corresponding two-stage Tobit estimation results provide suggestive evidence that teams use playing time as an investment in more junior players (Tables B.2 through B.7 for players younger than 22, 24, 26, and 28 years and older than 23 and 25 years, respectively). While the predicted grade significantly explains the playing time of older players, past performance seems to be less relevant for players younger than 22 (Figure II.6). Put differently, whereas old players are replaced if they perform poorly, young prospects are given a second chance. Given the suggestive evidence that playing time can substantially improve the performance of younger players, this strategy would be a rational response.

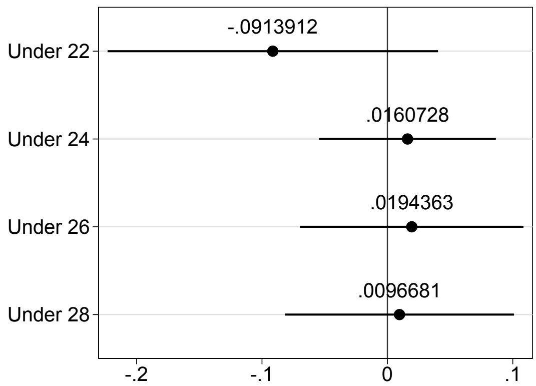


Figure II.5.: Point estimates for the effect of additional playing time on the grade of the following season for players younger than 22, 24, 26, and 28.

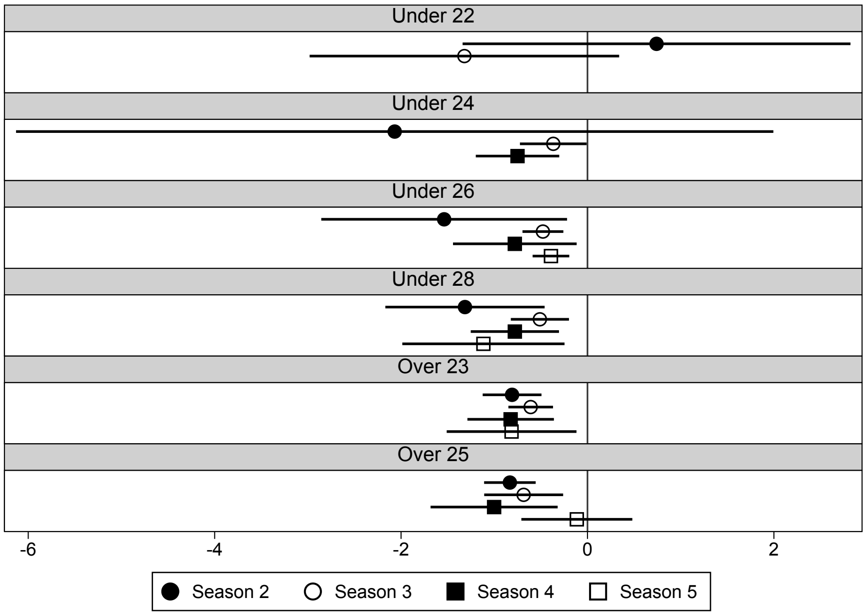


Figure II.6.: Effect sizes and standard errors of predicted grade on playing time for players younger than 22, 24, 26, and 28, and older than 23, and 25.

Robustness checks Bundesliga teams that enter European competitions may exhibit a different behaviour regarding their line-up decision. I expect them to give important players a rest during league matches to enable them to reach their top performance in international matches. The latter are often more important in terms of financial aspects and prestige. If the aforementioned players came with higher transfer fees, but were often rested from league games for the European matches, it would bias a potential sunk-cost effect downwards. I run the IV Tobit model from above, excluding teams that participate in international cups. Table II.5 shows the corresponding results of the second stage. It does not indicate a positive effect of transfer fees on playing time.

The grades from Kicker are sports journalists' assessments. These could be biased, taking into account transfer fees. Consider two otherwise identical and equally well performing players with different transfer fees. If the Kicker journalists rated a player who has been bought for a high fee (unjustly) better than his counterfactual, this would bias the estimate for transfer fees downwards. For that reason, I resort to alternative measures of performance that cannot fall prey to the sunk-cost fallacy. An alternative single measure

Table II.5.: Second-stage Tobit regression for teams that did not play international cups in the respective seasons.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.398**	-0.738***	-0.623*	-9.154
	(0.521)	(0.180)	(0.259)	(21.98)
Back-up grade$_{t-1}$	0.0274	0.131	0.257	-2.997
	(0.158)	(0.103)	(0.187)	(7.719)
Fee-bound transfer	-0.0281	0.0322	-0.0152	4.065
	(0.0702)	(0.0358)	(0.0778)	(10.31)
Transfer fee (in millions)	0.000111	0.0118	-0.00405	-0.495
	(0.0246)	(0.0133)	(0.00810)	(1.271)
Loan	-0.164			
	(0.136)			
Market value (in millions)	-0.00290	0.00539	0.0187	-0.621
	(0.0422)	(0.0218)	(0.0110)	(1.529)
Age	0.0578	-0.0228	0.109	-3.640
	(0.111)	(0.0729)	(0.0622)	(10.01)
Age squared	-0.00114	0.000153	-0.00179	0.0588
	(0.00211)	(0.00139)	(0.00113)	(0.162)
German (1=German)	-0.0957	-0.0336	0.108	-1.120
	(0.0539)	(0.0448)	(0.0799)	(3.071)
Google hits$_{t-1}$ (in thousands)	-0.0112	0.0351	-0.0819	1.110
	(0.0353)	(0.0348)	(0.0765)	(1.907)
Rank$_{t-1}$	-0.0153	0.00854	-0.0273	0.258
	(0.0148)	(0.0113)	(0.0174)	(0.797)
Constant	5.175***	2.068	-0.856	88.32
	(1.391)	(1.170)	(2.363)	(229.8)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	448	224	101	54

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Wald tests of exogeneity of the instrumented variable (predicted grade) are significant for Season 2 (p = .035) and 3 (p = .011), but not for Season 4 (p = .353) and 5 (p = .675).

of performance is the average points per match won by a team when a given player was fielded. Tables II.6 and II.7 report the IV Tobit results using points per match instead of Kicker grades as a proxy for performance. Controlling for performance with this purely observational measure produces the same insignificant effect of transfer fees on playing time. Again, a higher transfer fee is even associated with less playing time in season four.

As an additional robustness check, I follow the lead of Camerer and Weber (1999) and replace the aggregated measures (Kicker grades and points per match) with disaggregated measures (goals, assists, yellow, yellow-red, and red cards). I estimate Model II.5 for a restricted sample of outfield players (Table II.8). The disaggregated measures include the number of goals, which is certainly not a good predictor for the playing time of goalkeepers. While none of the coefficients of the individual disaggregated measures are significant, they are jointly significant. The estimates of the extensive and intensive margin of transfer fees are all insignificant, similar to the ones obtained in Tables II.4 and II.7. An analogous analysis for goalkeepers and defenders with goals conceded instead of goals shot does not indicate any significant coefficients either (Table B.8).[15]

Transfer fees, predicted performance, and playing time at match level

The OLS and IV Tobit estimates of the match-level analysis substantiate the results obtained at the seasonal level (Tables II.9 and II.10). In the aggregate, players' transfer fees do not seem to matter for how many minutes they play. The coefficients on the extensive and intensive margin are insignificant in both estimations.

A major advantage of using match level data is that it allows the inclusion of observations earlier than the second season. A sunk-cost effect might be more pronounced just after a player has been hired as the costs are then temporally closer. Therefore, I add an interaction term of transfer fees and the tenure of a player measured in match days. This makes the intensive variable of the transfer fee significant, yet negligible (Table II.11). There is indeed a small sunk-cost effect that decreases over time. Starting with match day 21 (the first 20 matches are excluded due to the lagged variables), the average player

[15] Goalkeepers only account for a very small sample size (e.g. 93 observations in Season 2) and neither the performance measures nor the transfer fee variables are significant.

Table II.6.: First-stage linear regression predicting points per match.

	Points per match			
	Season 2	Season 3	Season 4	Season 5
Points per match$_{t-1}$	0.221**	0.249**	0.298***	-0.121**
	(0.0773)	(0.0833)	(0.0644)	(0.0454)
Points per match$_{t-2}$		0.114*	0.0185	-0.0235
		(0.0539)	(0.0575)	(0.0472)
Points per match$_{t-3}$			0.0849	-0.0700
			(0.0608)	(0.0957)
Points per match$_{t-4}$				-0.00724
				(0.0299)
Back-up points per match$_{t-1}$	-0.106	-0.0112	-0.0849	-0.129
	(0.0687)	(0.0897)	(0.126)	(0.153)
Fee-bound transfer	0.118**	0.0162	0.0249	-0.0849
	(0.0418)	(0.0491)	(0.0860)	(0.119)
Transfer fee (in millions)	-0.0158***	-0.00648	0.00524	-0.000450
	(0.00474)	(0.00666)	(0.00840)	(0.00512)
Loan	0.0664			
	(0.0704)			
Market value (in millions)	0.0305***	0.0174*	0.0124	0.0157**
	(0.00652)	(0.00756)	(0.00694)	(0.00529)
Age	0.0306	0.120	0.0142	0.298
	(0.0484)	(0.112)	(0.128)	(0.171)
Age squared	-0.000450	-0.00227	-0.000479	-0.00441
	(0.000923)	(0.00217)	(0.00237)	(0.00297)
German (1=German)	0.0745*	0.0826	0.0477	0.124
	(0.0355)	(0.0460)	(0.0705)	(0.0731)
Google hits$_{t-1}$ (in thousands)	0.0197*	-0.0203	-0.0253***	-0.0380
	(0.00877)	(0.0353)	(0.00537)	(0.0217)
Champions League	0.195	0.279	0.539**	-0.184
	(0.117)	(0.193)	(0.173)	(0.203)
Europa League	0.219*	0.190	0.431**	0.257*
	(0.0865)	(0.104)	(0.165)	(0.102)
Rank$_{t-1}$	0.0200	0.0315	0.0361*	-0.00387
	(0.0116)	(0.0166)	(0.0162)	(0.0198)
Constant	0.267	0.206	1.070	-2.972
	(0.586)	(1.372)	(1.642)	(2.630)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	989	560	282	163

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table II.7.: Second-stage Tobit regression of the fraction of minutes played on predicted points per match.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted points per match	0.736**	0.717***	0.616**	-1.246
	(0.226)	(0.214)	(0.213)	(1.095)
Back-up points per match$_{t-1}$	-0.0799	-0.0299	-0.139	-0.154
	(0.0476)	(0.0722)	(0.0725)	(0.225)
Fee-bound transfer	0.0125	0.0178	0.0165	-0.0795
	(0.0419)	(0.0433)	(0.0498)	(0.171)
Transfer fee (in millions)	-0.00923	-0.00337	-0.0110**	0.00124
	(0.00617)	(0.00470)	(0.00388)	(0.00950)
Loan	-0.00565			
	(0.0834)			
Market value (in millions)	0.0220*	0.0144*	0.0192***	0.0400*
	(0.0100)	(0.00595)	(0.00400)	(0.0172)
Age	0.00491	-0.0599	0.0712	0.507
	(0.0307)	(0.0640)	(0.0531)	(0.431)
Age squared	-0.0000576	0.00115	-0.00120	-0.00769
	(0.000595)	(0.00122)	(0.000974)	(0.00685)
German (1=German)	-0.0264	-0.0252	0.0623	0.287**
	(0.0298)	(0.0446)	(0.0440)	(0.108)
Google hits$_{t-1}$ (in thousands)	-0.00223	0.00113	0.0122	-0.0924*
	(0.0154)	(0.0262)	(0.0118)	(0.0449)
Champions League	-0.202	-0.112	-0.464*	-0.436
	(0.106)	(0.131)	(0.188)	(0.275)
Europa League	-0.179*	-0.0822	-0.303	0.206
	(0.0805)	(0.0901)	(0.161)	(0.354)
Rank$_{t-1}$	-0.0121	-0.00626	-0.0399**	-0.00443
	(0.00864)	(0.00984)	(0.0133)	(0.0219)
Constant	-0.565	-0.463	-1.628	-6.108
	(0.497)	(0.915)	(1.061)	(5.559)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	989	560	282	163

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 (p = .193), all Wald tests of exogeneity of the instrumented variable (predicted points per match) are significant.

Table II.8.: Second-stage Tobit regression of the fraction of minutes played on predicted disaggregated measures for outfield players.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted goals	0.00442	-0.00443	0.0213	-0.00929
	(0.0679)	(0.0879)	(0.0174)	(0.0543)
Predicted assists	0.0240	0.0641	0.0580	0.0418
	(0.0490)	(0.0507)	(0.0412)	(0.0542)
Predicted yellow cards	0.217	0.0274	0.0425	-0.000389
	(0.365)	(0.216)	(0.0341)	(0.137)
Predicted yellow-red cards	-1.905	-0.549	0.243	0.672
	(4.598)	(1.916)	(0.834)	(0.869)
Predicted red cards	-0.294	3.242	-0.0397	-0.387
	(3.659)	(10.61)	(0.553)	(1.832)
Back-up goals$_{t-1}$	-0.0130	0.0108	-0.0286	-0.0896*
	(0.0389)	(0.0288)	(0.0207)	(0.0438)
Back-up assists$_{t-1}$	0.0130	0.0119	0.0593	0.114
	(0.0481)	(0.131)	(0.0345)	(0.172)
Back-up yellow cards$_{t-1}$	-0.0654	-0.136	-0.0832**	-0.0178
	(0.0555)	(0.400)	(0.0312)	(0.0459)
Back-up yellow-red cards$_{t-1}$	0.259	-0.878	-0.403	0.825
	(0.631)	(2.577)	(0.419)	(1.612)
Back-up red cards$_{t-1}$	0.0117	0.758	0.202	0.798
	(0.409)	(3.234)	(0.194)	(1.010)
Fee-bound transfer	0.00194	0.00232	0.0299	0.00665
	(0.0809)	(0.125)	(0.0495)	(0.0735)
Transfer fee (in millions)	0.000714	-0.0163	-0.00718*	0.00672
	(0.0141)	(0.0370)	(0.00335)	(0.00677)
Loan	-0.102			
	(0.431)			
Market value (in millions)	0.00249	0.0220	0.00704	0.00644
	(0.0289)	(0.0592)	(0.00805)	(0.00928)
Age	-0.0407	-0.0142	0.0597	-0.0357
	(0.266)	(0.0937)	(0.0591)	(0.473)
Age squared	0.000817	0.000375	-0.00105	0.00102
	(0.00518)	(0.00189)	(0.000988)	(0.00880)
German (1=German)	-0.0735	0.0593	0.0587	0.118
	(0.257)	(0.229)	(0.0574)	(0.162)
Google hits$_{t-1}$ (in thousands)	-0.00870	-0.0477	-0.00573	-0.0303
	(0.0598)	(0.143)	(0.00478)	(0.0398)
Champions League	-0.0577	-0.0149	0.0196	0.0362
	(0.179)	(0.222)	(0.0935)	(0.267)
Europa League	-0.0405	-0.168	0.0248	0.117
	(0.156)	(0.435)	(0.0922)	(0.179)
Rank$_{t-1}$	0.00146	0.0138	-0.00785	0.00393
	(0.0235)	(0.0733)	(0.00899)	(0.0214)
Constant	1.062	0.553	-0.856	0.209
	(4.919)	(1.537)	(0.978)	(7.703)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	896	501	245	136

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 4 (p = .083), all Wald tests of exogeneity of the instrumented variable (predicted goals, assists, and cards) are significant.

Table II.9.: Ordinary Least Squares regression of minutes played per match.

	Minutes played	
Match grade$_{t-1}$ if graded	-5.128***	(0.491)
Match grade$_{t-2}$ if graded	-2.269***	(0.189)
Match grade$_{t-3}$ if graded	-1.348***	(0.0991)
Match grade$_{t-4}$ if graded	-1.069***	(0.158)
Match grade$_{t-5}$ if graded	-1.032***	(0.134)
Match graded$_{t-1}$	44.74***	(2.934)
Match graded$_{t-2}$	18.79***	(0.923)
Match graded$_{t-3}$	10.65***	(0.522)
Match graded$_{t-4}$	9.756***	(0.639)
Match graded$_{t-5}$	10.59***	(0.779)
Match played$_{t-1}$	8.691***	(0.539)
Match played$_{t-2}$	3.128***	(0.576)
Match played$_{t-3}$	1.815***	(0.382)
Match played$_{t-4}$	-0.0744	(0.481)
Match played$_{t-5}$	0.301	(0.441)
Match backup grade$_{t-1}$ if graded	1.094**	(0.307)
Fee-bound transfer	0.692	(0.686)
Transfer fee (in millions)	0.0503	(0.0464)
Loan	-0.222	(1.175)
Market value (in millions)	0.476**	(0.167)
Age	1.622***	(0.435)
Age squared	-0.0281**	(0.00861)
German (1=German)	0.612	(0.399)
Google hits previous season (in thousands)	-0.122	(0.173)
Hiring coach	0.00770	(0.364)
Tenure in team	0.0347**	(0.00984)
Tenure in team squared	-0.0000740	(0.0000375)
Number of players in team	0.0628	(0.0357)
Champions League	0.0187	(0.635)
Europa League	0.00192	(0.436)
Rank difference	0.0895***	(0.0132)
Rank difference squared	0.00207	(0.00160)
Match day	0.162***	(0.0404)
Match day squared	-0.00350**	(0.000989)
Constant	-26.51***	(5.424)
Position Effects	Yes	
Team Effects	Yes	
Season Effects	Yes	
Adjusted R^2	0.524	
Observations	78490	

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table II.10.: IV Tobit regression of minutes played per match.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-85.80***	
	(9.154)	
Fee-bound transfer	1.156	0.00362
	(2.732)	(0.0163)
Transfer fee (in millions)	0.130	-0.00340
	(0.202)	(0.00176)
Back-up match grade$_{t-1}$	-3.394***	-0.0320***
	(0.737)	(0.00477)
Loan	-4.022	-0.0451
	(5.516)	(0.0530)
Market value (in millions)	0.181	-0.00498***
	(0.306)	(0.00130)
Age	7.736*	0.0264
	(3.707)	(0.0214)
Age squared	-0.157*	-0.000609
	(0.0713)	(0.000407)
German (1=German)	-2.314	-0.0474**
	(2.349)	(0.0145)
Google hits previous season (in thousands)	-0.119	0.00324
	(0.849)	(0.00375)
Hiring coach	-1.198	-0.0333**
	(1.360)	(0.0121)
Tenure in team	0.0654	-0.000463
	(0.0378)	(0.000277)
Tenure in team squared	-0.000143	0.000000740
	(0.000135)	(0.000000858)
Number of players in team	0.957*	0.00558*
	(0.375)	(0.00241)
Champions League	-2.677	0.0251
	(4.809)	(0.0311)
Europa League	-7.600**	-0.0503**
	(2.588)	(0.0194)
Rank difference	0.647***	0.00416***
	(0.0799)	(0.000628)
Rank difference squared	-0.000475	-0.0000599
	(0.00797)	(0.0000333)
Match day	0.442**	-0.000529
	(0.149)	(0.00109)
Match day squared	-0.0123**	-0.00000834
	(0.00387)	(0.0000283)
Constant	179.3**	3.788***
	(58.23)	(0.310)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

with a transfer fee of 1.72 million Euro *ceteris paribus* plays one and a half minutes more. Compared to the effect of a predicted increase in performance measured in grades of almost an entire match (86.95 minutes), the sunk-cost effect is minuscule.[16] In the aggregate regressions for the players' first to fifth seasons, this sunk-cost effect disappears (Table II.12; Table B.11 uses Google hits for the current season in Season 1 as the lagged variable is missing for many players in the first season).

In addition, coaches could only acknowledge transfer fees in their line-up decisions if the transfer fee is high relative to those of the other players in the roster. Therefore, I compute the transfer fee relative to the total transfer fees for the current roster. This specification cannot detect a significant sunk-cost effect either (Table B.12).

Coaches might also differ in the extent to which they commit the sunk-cost fallacy. While Haita-Falah (2017) does not find a significant relationship between cognitive ability and the tendency to honour sunk costs, there seems to be a correlation with age (Strough et al., 2008). Hence, I test whether more experienced, older coaches are less prone to acknowledge sunk costs. I find that the interaction effects of the transfer fee coefficients and the coaches' age are not significant (Table B.13).

Finally, I analyse whether a sunk-cost effect is only apparent for players who play under the same coach they debuted with. As described by Camerer and Weber (1999), it can be argued that new coaches may be able to ignore sunk costs incurred by predecessors (Schoorman, 1988; Staw et al., 1997; McCarthy et al., 1993). By contrast, Olivola (2018) provides evidence that the sunk-cost effect is an interpersonal phenomenon. Comparing Columns (1) and (2) in Table II.13, I find no clear evidence for either an interpersonal or an intra-personal sunk-cost effect. However, the switching signs of the coefficients of the variables related to the transfer fee should arouse suspicion and motivate further research.

Discussion

Despite its thoroughness, the analysis has certain limitations. First, Google hits are not a perfect proxy for player popularity. It is obvious that they also include coverage on bad performance and misconduct on and off the pitch. This could be detrimental to

[16] Table B.10 shows that decreasing the lag to five matches does not qualitatively change the result.

Table II.11.: IV Tobit regression of minutes played per match, interacting the transfer fee variables with the player's tenure in the team.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-86.95***	
	(8.681)	
Fee-bound transfer	4.766	0.0241
	(4.783)	(0.0281)
Transfer fee (in millions)	1.000***	0.00173
	(0.273)	(0.00196)
Fee-bound transfer × Tenure in team	-0.0404	-0.000226
	(0.0416)	(0.000286)
Transfer fee (in millions) × Tenure in team	-0.00777**	-0.0000463*
	(0.00263)	(0.0000209)
Back-up match grade$_{t-1}$	-3.396***	-0.0319***
	(0.735)	(0.00468)
Loan	-3.627	-0.0423
	(5.539)	(0.0531)
Market value (in millions)	0.0421	-0.00570***
	(0.336)	(0.00121)
Age	6.935	0.0217
	(3.787)	(0.0211)
Age squared	-0.142	-0.000518
	(0.0731)	(0.000403)
German (1=German)	-2.520	-0.0481***
	(2.332)	(0.0141)
Google hits previous season (in thousands)	0.363	0.00614
	(0.871)	(0.00486)
Hiring coach	-1.172	-0.0329**
	(1.353)	(0.0123)
Tenure in team	0.128**	-0.0000963
	(0.0420)	(0.000343)
Tenure in team squared	-0.000215	0.000000283
	(0.000127)	(0.000000810)
Number of players in team	0.972**	0.00564*
	(0.372)	(0.00237)
Champions League	-2.584	0.0255
	(4.883)	(0.0311)
Europa League	-7.886**	-0.0516**
	(2.582)	(0.0195)
Rank difference	0.654***	0.00417***
	(0.0780)	(0.000625)
Rank difference squared	0.0000253	-0.0000565
	(0.00818)	(0.0000338)
Match day	0.440**	-0.000539
	(0.150)	(0.00108)
Match day squared	-0.0124**	-0.00000845
	(0.00389)	(0.0000280)
Constant	189.6***	3.820***
	(55.20)	(0.299)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Tenure in team is measured in matches. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table II.12.: Second-stage Tobit regression of minutes played per match on a seasonal level, interacting the transfer fee variables with the player's tenure in the team.

	Minutes per match				
	Season 1	Season 2	Season 3	Season 4	Season 5
Predicted grade	-187.6***	-97.09***	-88.07***	-82.34***	-94.25***
	(40.10)	(12.23)	(12.66)	(11.20)	(16.43)
Back-up match grade$_{t-1}$	6.776*	-0.797	-3.324*	-4.127*	-9.844**
	(3.147)	(1.060)	(1.340)	(1.889)	(3.080)
Fee-bound transfer	28.00	-5.092	-8.395	-3.861	44.11*
	(33.65)	(7.769)	(12.75)	(29.12)	(17.32)
Transfer fee (in millions)	0.555	2.336*	-1.138	8.896	11.51**
	(8.016)	(0.940)	(1.543)	(4.856)	(4.379)
Fee-bound transfer × Tenure in team	-0.120	0.143	0.178	0.0436	-0.304*
	(0.703)	(0.138)	(0.156)	(0.268)	(0.144)
Transfer fee (in millions) × Tenure in team	-0.0759	-0.0340	0.00831	-0.0694	-0.0707*
	(0.105)	(0.0175)	(0.0203)	(0.0390)	(0.0295)
Loan	-182.3**	-4.768			
	(56.64)	(6.230)			
Market value (in millions)	-9.373	-0.0779	-0.0629	0.813	-0.784
	(5.871)	(0.746)	(0.541)	(0.789)	(0.422)
Age	37.84	0.876	6.430	17.83*	-12.60
	(43.78)	(5.555)	(5.968)	(7.912)	(7.703)
Age squared	-0.651	-0.0198	-0.130	-0.331*	0.173
	(0.968)	(0.104)	(0.118)	(0.153)	(0.134)
German (1=German)	-6.383	-6.396*	-1.676	0.669	-1.151
	(19.37)	(2.835)	(3.518)	(3.699)	(4.945)
Google hits previous season (in thousands)	51.13**	0.127	1.424	-2.826	3.882
	(17.81)	(1.081)	(2.345)	(1.870)	(2.129)
Hiring coach	13.98	-0.616	-5.020	-2.107	18.09***
	(17.09)	(2.288)	(4.671)	(6.477)	(4.966)
Tenure in team	0.881	0.292	-0.0756	0.421	0.0966
	(2.993)	(0.612)	(0.587)	(0.595)	(0.492)
Tenure in team squared	-0.00718	-0.00178	-0.000418	-0.00183	0.00113
	(0.0338)	(0.00665)	(0.00426)	(0.00287)	(0.00229)
Number of players in team	4.311	0.734	0.998	2.108	0.0928
	(3.826)	(0.580)	(0.574)	(1.317)	(0.641)
Champions League	9.240	0.999	-4.526	-10.29	-5.726
	(17.87)	(8.167)	(9.265)	(7.963)	(9.484)
Europa League	-16.90	-8.143	-2.158	-13.64	-24.77***
	(24.07)	(5.008)	(3.283)	(7.910)	(6.353)
Rank difference	1.505***	0.731***	0.284*	0.949***	0.370
	(0.381)	(0.133)	(0.129)	(0.218)	(0.316)
Rank difference squared	0.00989	0.00766	-0.00408	-0.00383	-0.00177
	(0.0261)	(0.0157)	(0.0141)	(0.0211)	(0.0257)
Match day	-0.902	-0.0211	0.512	0.725	0.596
	(3.026)	(0.408)	(0.397)	(0.527)	(0.819)
Match day squared	0.0316	-0.000369	-0.0123	-0.0180	-0.0237
	(0.0362)	(0.0104)	(0.0129)	(0.0126)	(0.0208)
Constant	-166.8	327.8***	166.4*	-30.78	552.6***
	(529.4)	(89.24)	(84.80)	(105.2)	(145.0)
Position Effects	Yes	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	2923	23954	15092	9614	6746

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 (5 in the first season) match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Tenure in team is measured in matches. All Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

Table II.13.: Second-stage Tobit regression of minutes played per match by coach-player relationship.

	(1) Under different coach Minutes per match	(2) Under same coach Minutes per match
Predicted grade	-82.04***	-101.8***
	(10.92)	(12.50)
Back-up match grade$_{t-1}$	-3.406***	-3.765***
	(1.008)	(1.021)
Fee-bound transfer	4.067	-3.962
	(2.746)	(4.110)
Transfer fee (in millions)	-0.101	0.701
	(0.191)	(0.600)
Loan	2.167	-6.927
	(8.174)	(7.820)
Market value (in millions)	0.324	-0.465
	(0.298)	(0.566)
Age	7.845	8.709
	(4.305)	(4.888)
Age squared	-0.159	-0.175
	(0.0838)	(0.0939)
German (1=German)	-3.115	-0.453
	(2.966)	(2.682)
Google hits previous season (in thousands)	-0.127	-0.0981
	(0.909)	(1.542)
Tenure in team	0.0500	0.122
	(0.0363)	(0.0862)
Tenure in team squared	-0.000128	-0.0000344
	(0.000119)	(0.000372)
Number of players in team	0.999	0.936
	(0.567)	(0.627)
Champions League	-0.964	2.308
	(5.657)	(5.100)
Europa League	-6.485*	-10.39*
	(3.127)	(4.554)
Rank difference	0.591***	0.730***
	(0.0835)	(0.112)
Rank difference squared	0.00849	-0.0154
	(0.00841)	(0.0152)
Match day	0.444*	0.472
	(0.193)	(0.315)
Match day squared	-0.0124**	-0.0139
	(0.00475)	(0.00860)
Constant	158.3*	247.5**
	(75.45)	(80.23)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Observations	45464	22603

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The first column is the regression for players who played under a different coach than the one who was in office when the player was acquired. The first column is the regression for players who played under the same coach who was in office when the player was acquired. The Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

jersey and ticket sales. Yet, with unknown players in particular, bad news could also have positive effects as they still increase a player's fame (Berger et al., 2010). Given that other data (e.g. on jersey sales) is not available on a detailed level, I am confident to provide a practicable yet convincing solution that might also be applied in future research.

Second, as a further control variable for player potential (in terms of sporting performance and marketing) I include Transfermarkt's market values. By nature, this variable correlates with actual transfer fees. Whereas the market value is an estimate of the value of a player for a team, transfer fees are determined by additional factors such as the remaining duration of a contract and can even be zero for highly valued but contract-less players. At the time of the observed transfers, the correlation of market values and transfer fees is 0.69. As market values are continuously updated, they retain explanatory power in some of the analyses, even after controlling for predicted or past performances. On a seasonal level (not only at the time of a transfer), the correlation between market values and transfer fees is only 0.61. Therefore, I am certain that the variable $MarketValue$ does not confound the results, but rather precludes an omitted variable bias. Moreover, excluding market values from the match-level IV Tobit estimation (Table II.10) does not make the transfer fee variables significant.

As discussed in Section II.1.2, existing studies have been able to uncover a sunk-cost effect in US professional sports that feature draft systems (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995). I am unable to empirically identify the reasons for the discrepancy between the behaviour under a draft system compared to a transfer market. Yet two accounts come to mind. First, transfer fees and bi-weekly salary payments could exhibit different degrees of salience and might vary with respect to the extent they represent sunk costs. In US sports, salaries are determined ex ante through a player's draft order and are therefore sunk. Bi-weekly or monthly payments could give the impression that these salaries are at the manager's discretion. Transfer fees are paid once, usually before the transferred player moves to the new team. It is conceivable that managers find it less difficult to identify these one-time payments as sunk costs and to ignore them compared to continuous but predetermined transactions. It would be interesting to test this hypothesis in the laboratory.

The second account are structures of the sports labour markets. In the US, several policies are aimed at balancing the league. In the rookie draft, teams pick new talents in reverse order of their past season's ranking. Hence, poorly performing teams are granted the opportunity to hire the players with the biggest prospects. A salary cap also helps to prevent a concentration of the best players among a few teams. Probably the most crucial difference is that US sports leagues are closed while teams in European leagues are subject to promotion and relegation (Andreff, 2011). The rather intense, deregulated market conditions in European professional sports leagues could produce an evolutionary process. Teams only survive at a professional level if they are able to act rationally. Behavioural biases such as the sunk-cost fallacy will push teams down the ranks and, due to relegation, out of the market. If market forces are not present or weaker as in US leagues, it might take longer for irrational behaviour to disappear. Falk and Szech (2013) experimentally document how market interaction can erode moral values. My results suggest that it could also alleviate behavioural biases. Future research should investigate the market conditions under which biases emerge or disappear.

Comparing the findings to results of the sunk-cost effect from the laboratory contributes to research on how professional experience in a given context can promote rational behaviour. Palacios-Huerta and Volij (2008), and Walker and Wooders (2001) show that professional football and tennis players, who have experience with interactions similar to those of mixed-strategy games, play closer to the equilibrium in these games than college students. Similarly, the sunk-cost fallacy could be detected in a number of experiments that primarily took students as subjects (e.g. Friedman et al., 2007). However, students rarely face situations that provide large incentives to overcome the sunk-cost fallacy. In contrast, irrational decisions are quickly penalised in professional sports. Top-level football coaches have to pick line-ups every match day. They are well advised to learn from their own experience and the observation of peers how honouring sunk-costs can reduce their chances of winning or even cost them their job.

II.1.6. Conclusion

I am unable to find evidence supporting the sunk-cost fallacy among professional football coaches on a seasonal level. This finding is robust to varying measures of performance (aggregated and disaggregated). It is in contrast to the results of a majority of previous articles that studied this behavioural bias in the context of professional sports (Camerer and Weber, 1999; Keefer, 2015, 2017; Staw and Hoang, 1995). A more detailed analysis on the match level reveals a sunk-cost effect. However, when compared to the effect of predicted performance on playing time, the effect of transfer fees is negligible and decreases with a player's tenure. Furthermore, I do not find that coaches with more experience are less prone to exhibit the sunk-cost fallacy. Finally, coaches do not seem to grant more playing time to players in whose transfer they were involved in. Hence, similarly to Borland et al. (2011) and Leeds et al. (2015), the results support rational behaviour in professional sports team management. Previous and predicted performance are the primary determinants of a player's time on the pitch in the German Bundesliga. Coaches and managers seem to be able to ignore the huge transfer fees they paid beforehand, as soon as players fail to live up to their expectations.

II.2. Cognitive Ability and the House Money Effect in Public Goods Games

II.2.1. Introduction and literature

Due to their characteristics of non-excludability and non-rivalry, public goods are of particular interest to economic scholars. The free-rider problem predicted by classic economic theory causes the private provision of public goods to be inefficiently low. Yet experiments on linear public goods games reveal substantial contributions, i.e. co-operation (Ledyard, 1995). Uncovering the key drivers of contributions in public goods games would help policy makers and researchers alike to understand how co-operation evolves and to overcome social dilemmas.

The house money effect in economic games

In this context, the origin of an endowment which can be contributed to the provision of a public good may be an important driver of contributions. As discussed in Chapter I, many individuals distinguish between money (or resources in general) obtained from different sources, violating the assumption of fungibility of money.[17] Particularly in experimental economics, the observation that unearned income is treated differently than earned income is referred to as the house money effect.[18] The common rationale is that windfall money evokes perceived property rights less strongly than earned money (see also Section I.2.2) and is therefore, *inter alia*, spent more generously (Cherry, 2001) and riskier (Cárdenas et al., 2014). The house money effect has been studied in various economic games. For dictator games, the results provide concordant evidence: subjects show less generosity when allocating earned income, both in the laboratory (Cherry, 2001; Cherry et al., 2002; Cherry and Shogren, 2008; Reinstein and Riener, 2012; Oxoby and Spraggon, 2008) and in

[17] Corresponding behavioural operations are called mental accounting (Thaler, 1985, 1990, 1999).

[18] The term *house money effect* was first coined by Thaler and Johnson (1990) referring to casino gamblers who are more willing to gamble with money they have just won and which, until its ultimate payout, is still considered as the casino's (or so-called house's) money. In experimental economics, the term has been generalised to describe the observation that endowment allocated to the participant is treated differently than endowment the participant had to work for (e.g. Clark, 2002; Danková and Servátka, 2015; Dannenberg et al., 2012).

the field (Carlsson et al., 2013).[19] Furthermore, Houser and Xiao (2015) provide evidence for the presence of a house money effect in trust games. Transfers by investors and trustees are lower if they have to decide over earned money.

By contrast, in public goods games, corresponding evidence remains mixed, rather indicating no effect (Spraggon and Oxoby, 2009). Most studies find that contributions in public goods games are independent of endowment origin (Clark, 2002; Cherry et al., 2005; Antinyan et al., 2015). Others indicate that contributions indeed depend on expended effort. Keeping subjects uninformed about the heterogeneity regarding the sources of endowment, Muehlbacher and Kirchler (2009) find that individuals who have to exert more effort contribute less. On the other hand, Harrison (2007) re-analyses the data of Clark (2002) and comes to a different conclusion by using a hurdle specification of a generalized estimating equation (GEE) approach. In doing so, Harrison (2007) accounts for the extensive and intensive dimension of the decision problem in public goods games. The decision making process whether to contribute anything at all might be determined in another way than the decision of how much to give. Furthermore, using a GEE approach he is able control for possible correlations of individual responses over time. The results suggest that individuals have a 8.2 percentage points higher propensity to free-ride when playing with windfall money, compared to a sample average of 27 percent. Yet on the intensive margin, there is no house money effect.

Cognitive ability and economic decision making

However, to date the discussion has ignored a major factor that may be crucial for explaining the house money effect. The complexity of economic decisions requires analytical reasoning. Since humans vary in their cognitive abilities (Frederick, 2005), these reasoning skills are fundamental determinants of heterogeneous responses to economic problems. Analysing a sample of more than 1,000 adults living in Germany, Dohmen et al. (2010) show that cognitive ability highly correlates with risk and time preferences. Furthermore,

[19] Only Luccasen and Grossman (2017) obtain an opposing result. They find that warm-glow giving to charity or philanthropic institutions is higher for earned endowment. The authors hypothesise that subjects derive more utility from donating earned money than an equally sized windfall gain.

subjects appear to be less self-serving in dictator games when being under cognitive load (Schulz et al., 2014). By contrast, Chen et al. (2013) conclude that cognitive ability is positively correlated with generosity in dictator games. Specifically, recent research also suggests an effect of cognitive processes on co-operation. Interestingly, there exist both studies that find a positive (Clark, 1998; Lohse, 2016) and a negative link (Kanazawa and Fontaine, 2013; Nielsen et al., 2014) between cognitive skills and co-operation.

Regarding the house money effect, cognitive abilities appear to be equally relevant. Many researchers suggest that people apply strategies like choice bracketing, i.e. making each choice in isolation, or mental accounting to simplify economic decisions (Thaler, 1999; Read et al., 1999). Read et al. (1999, p. 187) argue that cognitive limitations are a key determinant for individuals to bracket narrowly, thereby facilitating decision making. Correspondingly, when spending income, individuals with low cognitive abilities seem to be less capable to abstract from the source of income. By contrast, subjects with higher cognitive capacity are expected to be less reliant on applying heuristic simplification methods. Instead, they are more capable to consider potential consequences and spillover effects of decisions and thus are more likely to keep track of the entire available budget when spending income. Thus, if the differentiation and discrimination of income sources is the result of individuals having to simplify decision making, this suggests that a subject's cognitive capacity may also be associated with the extent to which she exhibits the house money effect. An experiment by Abeler and Marklein (2017) supports this prediction. They find that individuals with lower cognitive skills have a higher propensity to violate the assumption of the fungibility of money.

In this section, I examine whether individuals differ in the degree to which they exhibit the house money effect in a public goods game. In doing so, I build on two documented facts: (1) that unearned income generally appears to be donated or shared more easily (e.g. Cherry, 2001), and (2) that violations of fungibility negatively correlate with cognitive skills (e.g. Abeler and Marklein, 2017).

Hypothesis

On the basis of these observations, I hypothesise that in a public goods game contributions by individuals with low cognitive skills should be smaller the higher the share of earned income. By contrast, I expect the origin of income to have less or no effect on contributions by individuals with high cognitive skills.

The results indeed demonstrate that subjects' contributions depend on an interplay of cognitive abilities and endowment origin. While a house money effect exists for subjects with lower cognitive ability, there is no such effect for those with high cognitive ability. The former contribute more when income was allocated to them and less when income was obtained by effort. Contrarily, the latter contribute the same amount independent of income type.

I proceed as follows. In Section II.2.2 I describe the experimental design. Section II.2.3 presents results as well as further robustness checks. I conclude and discuss potential implications of the results in Section II.2.4.

II.2.2. Experimental Design

The experiment consisted of four parts: (1) a real effort task, (2) a three person linear public goods game, (3) the cognitive reflection test (CRT) developed by Frederick (2005), and (4) a questionnaire on demographic information. It was conducted with first year business administration students using paper and pencil at the Technical University of Munich, Germany.[20] Although there is evidence that business and economics students are different from the rest of the population (Meier and Frey, 2004; Kirchgässner, 2005; McCannon and Peterson, 2015; Bauman and Rose, 2011), the sample is well-suited for the analysis. First, respective studies find level differences in social preferences between students of different subjects. Since the main focus of this study is to detect an interaction effect, this would only affect the analysis if the overall level of contributions was too low or too high to find an interaction. Second, students within one discipline are less heterogeneous. Hence, if I am able to establish an interaction effect in that sample, the

[20] Instructions translated to English are provided in Appendix D.1.

result can be considered as a lower bound of the effect. Cognitive ability in particular can be assumed to vary substantially more in the entire population.

Real effort task

At the beginning of the experiment, the participants were randomly divided into three treatment groups. Each group had to colour in a different number of circles out of a total of 150.[21] This task was used to simulate a cognitively non-demanding real effort task. Hereby, depending on the treatment, a fraction of the 150 circles had already been filled in on behalf of the participants, sparing them a part of the effort. More precisely, the subjects had to colour in either 15 circles with 135 circles already being filled in (*Low Effort*), 75 circles with the other half being filled in (*Medium Effort*[22]), or 135 circles with only 15 circles being filled in (*High Effort*). Hence, subjects in the *Low Effort* condition, for instance, only had to provide the effort of filling in 10 percent of the total 150 circles in order to earn the endowment. All participants were informed about these three different treatments.

In total, 161 students participated in the experiment. Seven participants did not finish the task and were excluded from the experiment. This resulted in 65, 38, and 51 subjects in the *Low*, *Medium*, and *High Effort* treatment, respectively.[23] For having coloured in all circles appropriately, all subjects received the same endowment of 100 tokens (10 tokens = 0.60 Euro). As the participants had to colour in different numbers of circles, this induced different proportions of earned and allocated income (i.e. either 10, 50, or 90 percent of the total income was earned by effort).

[21] See Figure D.1 on the Task Sheet in Appendix D.1 for the *High Effort* treatment which required participants to fill in 135 circles.

[22] The *Medium Effort* treatment was included as a manipulation check. As expected, contributions by subjects in the *Medium Effort* treatment are between those of the *Low* and the *High Effort* treatment, for the pooled sample as well as for the subjects with a low and a high CRT score separately.

[23] Two, one, and four subjects were dropped from the *Low*, *Medium*, and *High Effort* treatment, respectively.

Public goods game

Following the task, individuals could decide on which proportion of their endowment to invest in a one-shot three-person linear public good with a marginal per capita return of 0.5. Therefore, the pay-off function π_i of player i with $i \in \{1, 2, 3\}$ who contributes $\theta_i \in \{0; 100\}$ is given by:

$$\pi_i = (100 - \theta_i) + 0.5 \cdot \sum_{j=1}^{3} \theta_j \tag{II.6}$$

with $\theta_j \in \{0; 100\}$ being the contribution of player $j \in \{1, 2, 3\}$. Importantly, subjects did not know the required effort levels of the other two players in their group. However, they knew that all combinations of the three treatments were possible.

Cognitive reflection test

Subsequently, the students had to perform the CRT, which I used in order to elicit cognitive ability. It contains three questions that all have an intuitive, yet incorrect answer, and one correct answer that requires deliberation. Despite the test's brevity, it significantly correlates with results from more sophisticated tests such as the *Wonderlic Personnel Test* or the *Wechsler Matrix Test* (Frederick, 2005; Toplak et al., 2011, 2014). It is also popular and frequently used in economics experiments, (e.g., Haita-Falah, 2017), including public goods experiments (Nielsen et al., 2014; Lohse, 2016). The test is particularly suitable in a setting with two different types of endowment. It aims at separating types that answer intuitively from those answering deliberately. Participants are making use of an endowment from two different sources, so it might be reasonable at first glance to use these sources differently as well. However, further cognitive reflection should make individuals realise that the two income types are perfect substitutes.

Finally, participants had to complete a questionnaire on demographic information.

Payment

After the experiment, a total of 18 participants were randomly chosen and assigned into groups of three to receive the resulting pay-off. Nevertheless, the participants remained completely anonymous. The composition of groups was only announced using participation numbers. Also, final payments were subsequently done in private while ensuring that subjects could not see which participants were drawn or formed a group. Both was communicated at the beginning of each session. I also informed the participants prior to the experiment that the chances of being drawn were at least ten percent. Following Dohmen et al. (2010, p.1245) this ensures incentive compatibility although ultimately not everyone is being paid. On average the selected students earned 7.68 Euro.

II.2.3. Results

On average subjects contribute around 51 percent of their initial endowment. In the CRT 40 percent answered all three questions correctly, followed by 32 percent with two, 16 percent with one, and 12 percent with zero correct answers.[24]

Contributions by endowment origin

In line with the existing literature, contributions in the public goods game do not differ significantly across treatments, i.e. effort levels. Of their equally high endowment, subjects contribute 55 percent in the *Low* and 48 percent in the *High Effort* treatment ($p = .210$, independent t-test[25]; $p = .230$, Mann-Whitney-U test; Figure II.7).

Contributions by cognitive ability

For the analysis of contributions by cognitive ability I use a dummy variable that divides the sample into two subgroups: individuals with high and low cognitive skills. The CRT

[24]Due to the fact that the sample consists of first year students who have not yet had opportunities to participate in experiments, I am confident that they did not know the test and preclude concerns of familiarity raised by recent studies (e.g. Toplak et al., 2014).

[25]Unless otherwise stated, every time an independent t-test is conducted, I consider a two-tailed t-test. Furthermore, with reported t-tests, corresponding Shapiro-Wilk tests of normality and two-sample variance-comparison tests do not reject normality or equal variances.

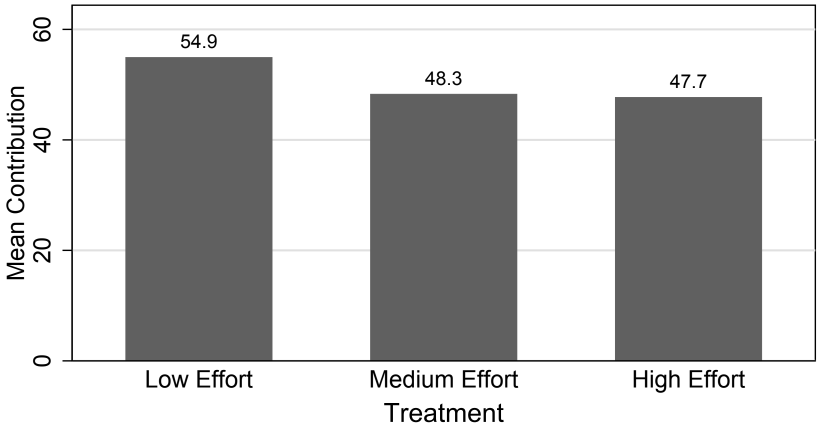


Figure II.7.: Mean contributions by treatment group.

includes three questions; the dummy *High CRT* turns one if all questions are answered correctly (40 percent of the sample) and zero otherwise (60 percent). Across treatments, contributions of individuals with a high CRT score are not significantly different to those of their low CRT counterparts, both contributing around 51 percent (p = .885, t-test with unequal variances; p = .826, Mann-Whitney-U test, Figure II.8). This suggests that subjects with low and high cognitive ability do not differ in how much they contribute to a public good when the dominant strategy is to give nothing.

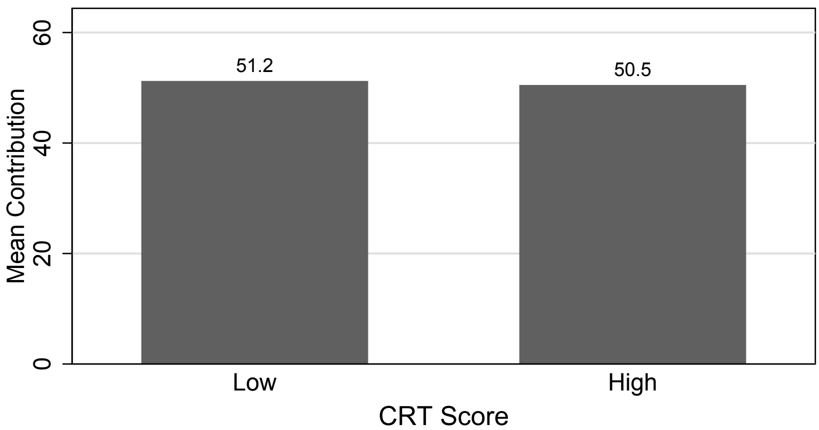


Figure II.8.: Mean contributions by CRT scores.

Contributions by endowment origin and cognitive ability

In fact, a breakdown of contributions by treatment and CRT results yields an interesting pattern. Behaviour differs, but the effects mostly cancel out when pooling treatments. As depicted in Figure II.9, I find that subjects' contributions depend on the interaction of their cognitive abilities and their endowment source. On the one hand, individuals with a low CRT score contribute 62.9 percent in the *Low Effort* treatment and 43.9 percent, almost one third less, in the *High Effort* treatment. An independent t-test shows that this difference is significant ($p = .008$, t-test; $p = .016$, Mann-Whitney-U test) and demonstrates that a low CRT score is associated with behaviour exhibiting the house money effect. On the other hand, contributions by individuals with a high CRT score do not differ significantly by endowment source, 48 percent in the *Low* versus 55 percent in the *High Effort* treatment ($p = .496$, t-test; $p = .578$, Mann-Whitney-U test). This suggests that subjects with higher cognitive ability are less likely to exhibit the house money effect.

Interestingly, the endowment source determines whether subjects with a low CRT score appear to be more or less co-operative than subjects with a high CRT score. In the *Low Effort* treatment, contributions by subjects with low CRT scores are 14.8 percentage points higher than contributions by subjects with high scores, 62.9 versus 48.1 percent ($p = .044$, t-test; $p = .053$, Mann-Whitney-U test). Thus, subjects with low CRT scores behave relatively more co-operatively with unearned income. Contrarily, in the *High Effort* treatment, their contributions are 10.8 percentage points lower than those of subjects with high scores (43.9 versus 54.7 percent). However, this difference is not statistically significant ($p = .250$, t-test; $p = .295$, Mann-Whitney-U test). Hence, while being relatively more co-operative than subjects with high CRT scores in the *Low Effort* treatment, subjects with lower CRT scores behave similarly to the high CRT scorers and possibly less co-operative when using earned income. An independent t-test shows that this interaction of treatment and CRT scores is statistically significant ($p = .029$).

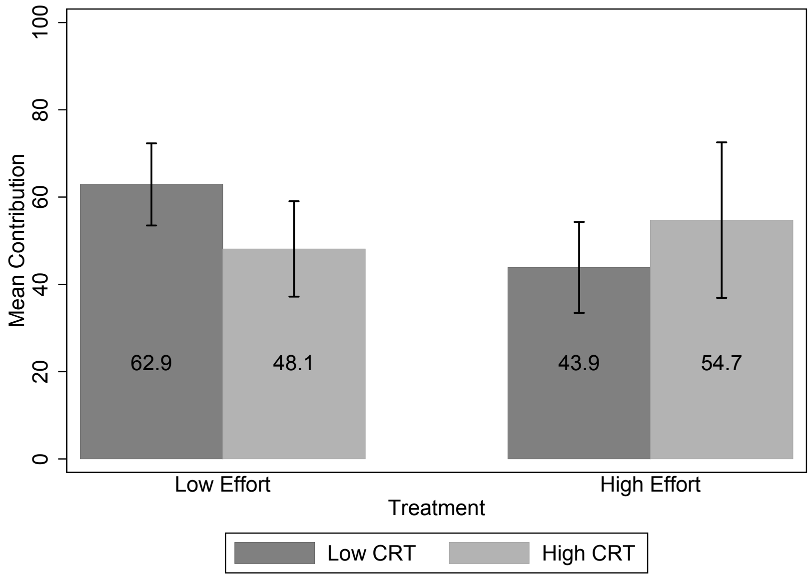


Figure II.9.: Mean contributions by CRT score and treatment group. Error bars indicate 95% confidence intervals.

Multivariate analysis

The interaction effect is also robust to controlling for gender, age, and session effects. To that end, similar to Harrison (2007) I resort to the Hurdle model (II.7) that accommodates the extensive and intensive margin of decisions in public goods games. As depicted by Figure II.10, a large fraction of subjects (10 percent) decides to contribute zero to the public good. Given a subject contributes a positive amount, the contributions approximately follow a normal distribution.

The Hurdle model therefore has two components. First, it estimates whether a subject contributes anything at all (II.8). Second, it fits a linear outcome model (II.9). It can be

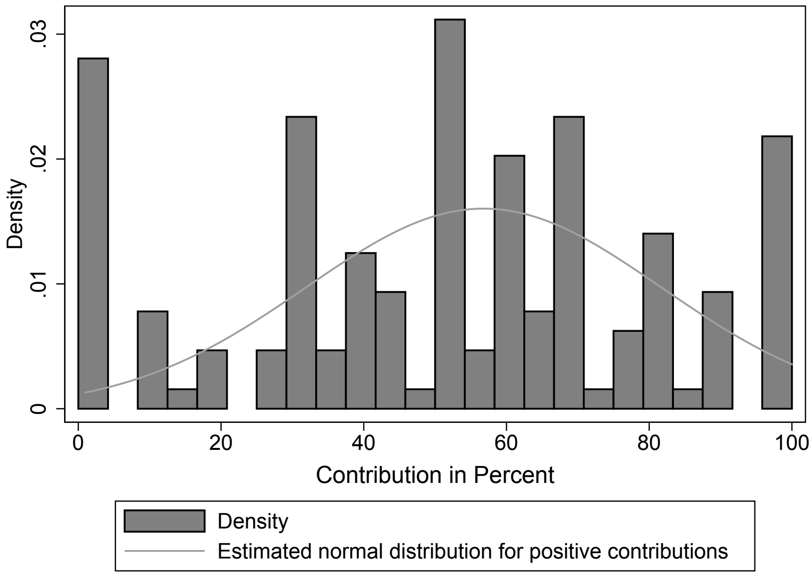


Figure II.10.: Histogram of contributions and estimated normal distribution for positive contributions.

characterised by the following set of relations (see also Botelho et al., 2009, for a discussion of the Hurdle model).

$$y_i = s_i h_i^*, \tag{II.7}$$

$$\text{with } s_i = \begin{cases} 1 & \text{if } \mathbf{x}_i\gamma + \epsilon_i > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{II.8}$$

$$\text{and } h_i^* = \mathbf{x}_i\beta + \nu_i, \tag{II.9}$$

where y_i is the estimated contribution. s_i is the selection variable which is 1 if a subject is estimated to contribute a positive amount and 0 otherwise. h_i^*, the latent variable, is a subject's expected contribution, conditional on the contribution being positive. $\mathbf{x}_i$ is the vector of explanatory variables. I include the same variables in both the selection and the outcome model. Thus, γ and β are the corresponding vectors of coefficients, and ϵ_i and ν_i are error terms.

Table II.14 reports the estimation results using the dummy for CRT score. Computing marginal effects confirms the interaction effect and the differences within treatments observed in the non-parametric analysis. Individuals with low CRT scores contribute 22.2 percentage points less in the *High* than in the *Low Effort* treatment (marginal effect of the variable *High Effort* for *Low CRT* subjects, $p = .006$). For subjects with high CRT scores, the difference is positive (they contribute more), but not significant (7.8, marginal effect of the variable *High Effort* for *High CRT* subjects, $p = .437$). The difference between individuals with low and high CRT scores is 16.0 (marginal effect of the variable *High CRT*, $p = .024$) in the *Low Effort* treatment and -12.7 (marginal effect of the variable *High CRT*, $p = .179$) in the *High Effort* treatment. Surprisingly, none of the variables has a significant effect on the extensive margin.

Table II.14.: Maximum likelihood estimates of the Hurdle model of contributions using the binary treatment variable (*High Effort*) and the binary CRT variable *High CRT*.

	Contribution	Selection (Probit)
High Effort	-21.474*	-0.620
	(8.605)	(0.629)
High CRT	-11.746	-0.836
	(7.145)	(0.573)
High Effort × High CRT	30.617**	0.670
	(11.565)	(0.763)
Age	1.603	-0.101
	(1.316)	(0.074)
Male	7.077	-0.863
	(5.977)	(0.505)
Constant	30.724	4.859**
	(27.811)	(1.754)
Session Effects	Yes	Yes
N	116	

Notes: The variable *High Effort* is a binary variable, which takes a value of one if the subject is assigned to the *High Effort* treatment and zero for the *Low Effort* treatment. Therefore, the regression is run on 116 observations of the *Low* and *High Effort* treatment, excluding those of the *Medium Effort* treatment. *High CRT* is equal to 1 if the subject has answered all CRT questions correctly and 0 otherwise. Male is equal to one for males and zero otherwise.

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table II.15 summarises the contributions by individuals with low and high CRT results in the *Low* and *High Effort* treatment as estimated by the Hurdle model. It further illustrates that subjects with low CRT scores exhibit the house money effect, giving more in the *Low* than in the *High Effort* condition. By contrast, contributions by subjects with high CRT scores are statistically indistinguishable. If anything, the resulting difference points towards an inverse house money effect. Table II.15 also confirms that cognitive ability has an impact on co-operative behaviour, albeit indirectly. Subjects with low CRT scores give more than their high CRT counterparts in the *Low Effort* treatment, but less in the *High Effort* treatment. Therefore, as these differences partly cancel out, it seems that cognitive ability does not affect co-operative behaviour when pooling treatments. Hence, cognitive ability influences an individual's propensity to exhibit the house money effect, thereby also affecting her contributions to the public good.

Table II.15.: Contributions as estimated by the Hurdle model.

	Low Effort	High Effort	p-Value
Low CRT	65.3	43.0	0.006
High CRT	47.3	55.1	0.437
p-Value	0.024	0.179	

Robustness checks

I run several robustness checks to further confirm these results. I first check if I obtain the same results without separating the extensive and intensive margin (Specification (1) in Table D.1 in the Appendix). In order to test whether the results are driven by including the CRT scores as a binary variable, I run an OLS regression replacing the dummy with a continuous variable (*Correct*) that indicates the number of correctly answered CRT questions (Specification (2) in Table D.1 in the Appendix). Finally, while I have excluded the *Medium Effort* treatment so far, I treat effort as a continuous variable and therefore include corresponding observations in Specification (3). Across specifications, significance levels and directions are similar for the treatment variable (*High Effort*), for the measures of cognitive ability (the dummy *High CRT* indicating that a subject has answered all

CRT questions correctly and *Correct* as the total number of correct answers), and the interaction effect (*High Effort* × *High CRT* and *High Effort* × *Correct*).

In addition to the CRT as a measure for cognitive ability or ability to overcome one's faulty intuition, I test whether the interaction effect exists when taking the students' final math grade as an explanatory variable as proposed by Abeler and Marklein (2017). The results also point towards an interaction effect. However, the coefficients are not statistically significant (see Table D.2 and Figure D.2 in the Appendix for the estimated coefficients and the correspondingly predicted contributions in a Hurdle model.)

To conclude, subjects' contributions in a public goods game depend on an interplay of cognitive ability and endowment origin. While a house money effect exists for subjects with low CRT scores, there is no such effect for those with high scores. The former contribute more when their income has been allocated to them and less when their income has been obtained by effort. On the contrary, the latter contribute the same amount independent of the type of income. These results also explain why there is suggestive but not significant evidence for a house money effect when pooling all subjects. As shown in Figure II.7, subjects contribute 55 percent under the *Low Effort* condition and 48 percent under the *High Effort* condition.

Discussion

The results raise the question whether studies that find no significant effect of effort in public goods games but do not account for cognitive ability should at least find suggestive evidence for a house money effect. In fact, Antinyan et al. (2015) obtain a negative but insignificant effect of effort on contributions in their *No Punishment* treatment as well as in their *Punishment* treatment without controlling for an interaction of time and effort. Although Cherry et al. (2005) detect a positive yet insignificant effect of effort on absolute contributions, effort negatively yet also insignificantly reduces contributions in relative terms. Finally, Clark (2002) finds suggestive but insignificant evidence for a house money effect in the first round of his repeated public goods game as well as when he pools all rounds.

II.2.4. Conclusion

Public goods have always received high levels of attention in social science. Especially during the last decades, experimental studies have frequently used public goods games to shed light on the dynamics behind co-operative behaviour (see Zelmer, 2003, for an overview on public goods games).

This is the first study to show that contributions to a public good depend on an interplay of income origin and cognitive skills. The result has implications for the interpretation of past and future experiments in which subjects are either given or earn their endowments. Corresponding findings might not be generalisable, but only be true for the respective experimental design. In particular, the results imply that conclusions which correlate cognitive ability with economic behaviour[26] can be reversed if the experimental design changes. In the experiment, subjects with a high CRT score behave more co-operatively in the *High Effort* treatment but less so in the *Low Effort* treatment. Thus, the external validity of respective results might particularly be questioned, considering populations that are more cognitively heterogeneous than students. In economics, the participant pool often consists solely of university students who are likely to be rather homogenous (Frederick, 2005) and to have above average cognitive abilities. Nevertheless, I am able to identify an interaction effect even within this group.

Furthermore, contributions in a public goods game can *inter alia* be regarded as subjects' preferences for redistribution. Thus, the results are relevant for studying redistributive taxation and tax compliance (e.g. Bühren and Kundt, 2014).

Finally, team production can also be compared to a public goods game (Alchian and Demsetz, 1972). Contributions by one team member benefit all other team members. For this reason, team production is equally exposed to a free-rider problem. Hence, a variation in how agents receive their resources they can use as production inputs (e.g. information) can alter team member's propensity to co-operate.

[26]This includes conclusions that subjects with higher cognitive ability are more (Chen et al., 2013) or less (Schulz et al., 2014) generous or more (Clark, 1998; Lohse, 2016) or less (Kanazawa and Fontaine, 2013; Nielsen et al., 2014) co-operative.

Conclusion

In this dissertation, I examined behaviour that violates the assumption of fungibility. On the basis of psychological ownership, a concept from psychological research, I presented a psychologically founded explanation for violations of fungibility. By introducing what I termed source-dependent preferences, I generalised consumer theory such that it can accommodate violations of fungibility, including the proposed psychological mechanism. Using calibrations I put existing empirical evidence into perspective. I also demonstrated that policy can use this behaviour to increase welfare. The second chapter comprises two studies that provide additional evidence regarding violations of fungibility on the labour market and in co-operative behaviour. The first study used data from professional sport and showed that sunk costs incurred in recruitment have a statistically significant but economically negligible impact on line-up decisions. By contrast, the second study presented an experiment showing that the effort made for an income has a negative influence on the co-operative behaviour of the subjects. However, this effect decreases with the subject's cognitive ability.

Despite concerns it might be incompatible with violations of fungibility, Chapter I demonstrates how consumer theory can be modified to accommodate corresponding behaviour. The empirical evidence emphasises the importance of taking source-dependent preferences into account when considering policy alternatives, for which the presented framework provides one approach. Calibrations across existing studies suggest that relatively small transfers are particularly effective. This speaks in favour of multiple small targeted transfers rather than a single large one. Future research could test this prediction empirically. Generally, Chapter I proposes a tentative application where redistribution through labelled transfers can increase welfare in the context of consumption externalities. Further extensions could investigate optimal redistribution with source-dependent preferences for heterogeneous populations and when people vote for redistribution.

In Section II.1, using data from professional football in Germany, I investigated whether player utilisation is affected by initially paid transfer fees. Unlike the majority of previous articles that studied the sunk-cost fallacy in the context of professional sports, I am unable to find evidence supporting this behavioural bias on a seasonal level. A more detailed analysis on the match level reveals a sunk-cost effect which, however, is economically negligible and decreases with a player's tenure. The results therefore corroborate a rational behaviour among professional sports team managers. Two accounts that might explain the difference to the existing evidence are suggested: the higher degree of salience of large one-time transfer fee payments in German professional football compared to bi-weekly salary payments in US sports and the more intense, less regulated competition in German professional football. The finding also supports that experience and professionalisation promote rational behaviour. Both experimental and empirical research could shed further light on the impact of salience, experience, and competition on the occurrence of sunk-cost effects.

The experiment presented in Section II.2 provides three central findings. First, it shows that subjects' contributions to a public good depend on an interplay of cognitive abilities and endowment origin. Second, violations of fungibility in the form of a house money effect can only be found for subjects with low CRT scores. They contribute more in a public goods game when income was allocated to them and less when income was obtained by effort. Third, in contrast to subjects with low CRT scores, subjects with high CRT scores contribute the same amount independent of income type. The findings have implications for redistribution, team production, and experimental designs. Future research could investigate how output in teams depends on the team's composition and on how team members' resources are provided. For a theoretical perspective, Chapter I provides a framework to explore mechanism design for such teams.

Appendices

Appendix A.

Appendix to Chapter I

A.1. Proof of Proposition 1

Proof of (i): By the completeness, $(x, I) \succsim_S (x, I)$ for every $x \in \mathcal{X}$ and a given income composition $I \in \mathcal{I}$. Hence there is no $x \in \mathcal{X}$ such that $(x, I) \succ_S (x, I)$. Suppose that $(x, I) \succ_S (x^{'}, I)$ and $(x^{'}, I) \succ_S (x^{''}, I)$, then $(x, I) \succ_S (x^{'}, I) \succsim_S (x^{''}, I)$. By (iii) of Proposition 1, which is proved below, we have $(x, I) \succ_S (x^{''}, I)$.

Analogously, there is no $I \in \mathcal{I}$ such that $(x, I) \succ_S (x, I)$. Suppose that $(x, I) \succ_S (x, I^{'})$ and $(x, I^{'}) \succ_S (x, I^{''})$, then $(x, I) \succ_S (x, I^{'}) \succsim_S (x, I^{''})$. By (iii) of Proposition 1, which is proved below, we have $(x, I) \succ_S (x, I^{''})$. Hence $\succ_S$ is transitive. Property (i) is now proved. □

Proof of (ii): Since $(x, I) \succsim_S (x, I)$ for every $x \in \mathcal{X}$ and a given income composition $I \in \mathcal{I}$, $(x, I) \sim_S (x, I)$ for every $x \in \mathcal{X}$ and the given income composition $I \in \mathcal{I}$ as well. Thus $\sim_S$ is reflexive. Suppose that $(x, I) \sim_S (x^{'}, I)$ and $(x^{'}, I) \sim_S (x^{''}, I)$. Then $(x, I) \succsim_S (x^{'}, I)$, $(x^{'}, I) \succsim_S (x^{''}, I)$, $(x^{'}, I) \succsim_S (x, I)$ and $(x^{''}, I) \succsim_S (x^{'}, I)$. By the transitivity, this implies that $(x, I) \sim_S (x^{''}, I)$ and $(x^{''}, I) \sim_S (x, I)$. Thus $(x, I) \sim_S (x^{''}, I)$. Hence $\sim_S$ is transitive. Suppose (x, I) that $\sim_S (x^{'}, I)$. Then $(x, I) \succsim_S (x^{'}, I)$ and $(x^{'}, I) \succsim_S (x, I)$. Thus $(x^{'}, I) \succsim_S (x, I)$ and $(x, I) \succsim_S (x^{'}, I)$. Hence $(x^{'}, I) \sim_S (x, I)$.

Analogously, suppose that $(x, I) \sim_S (x, I^{'})$ and $(x, I^{'}) \sim_S (x, I^{''})$. Then $(x, I) \succsim_S (x, I^{'})$, $(x, I^{'}) \succsim_S (x, I^{''})$, $(x, I^{'}) \succsim_S (x, I)$ and $(x, I^{''}) \succsim_S (x, I^{'})$. By the transitivity, this implies that $(x, I) \sim_S (x, I^{''})$ and $(x, I^{''}) \sim_S (x, I)$. Thus $(x, I) \sim_S (x, I^{''})$. Hence $\sim_S$ is transitive. Suppose (x, I) that $\sim_S$ $(x, I^{'})$. Then $(x, I) \succsim_S (x, I^{'})$ and $(x, I^{'}) \succsim_S (x, I)$. Thus $(x, I^{'}) \succsim_S (x, I)$ and $(x, I) \succsim_S (x, I^{'})$. Hence $(x, I^{'}) \sim_S (x, I)$. Thus $\sim_S$ is symmetric. Property (ii) is now proved. □

Proof of (iii): Since $(x^{'}, I) \succ_S (x^{''}, I)$ implies $(x^{'}, I) \succsim_S (x^{''}, I)$, the transitivity implies that $(x, I) \succsim_S (x^{''}, I)$. Suppose that $(x^{''}, I) \succsim_S (x, I)$. Since $(x^{'}, I) \succsim_S (x^{''}, I)$, the transitivity then implies that $(x^{'}, I) \succsim_S (x, I)$. But this contradicts $(x, I) \succ_S (x^{'}, I)$. Thus we cannot have $(x^{''}, I) \succsim_S (x, I)$. Hence $(x, I) \succ_S (x^{''}, I)$.

Analogously, since $(x, I^{'}) \succ_S (x, I^{''})$ implies $(x, I^{'}) \succsim_S (x, I^{''})$, the transitivity implies that $(x, I) \succsim_S (x, I^{''})$. Suppose that $(x, I^{''}) \succsim_S (x, I)$. Since $(x, I^{'}) \succsim_S (x, I^{''})$, the transitivity then implies that $(x, I^{'}) \succsim_S (x, I)$. But this contradicts $(x, I) \succ_S (x, I^{'})$. Thus we cannot have $(x, I^{''}) \succsim_S (x, I)$. Hence $(x, I) \succ_S (x, I^{''})$. □

A.2. Proof of Proposition 2

To prove this proposition, we show that if there is a utility function that represents preferences $\succsim_S$ then $\succsim_S$ must be complete and transitive.

Completeness. Because $u(\cdot)$ is a real-valued function defined on X and $\mathbb{R}^n$, it must be that for any $x, x^{'} \in \mathcal{X}$, either $u(x, I) \geq u(x^{'}, I)$ or $u(x^{'}, I) \geq u(x, I)$, and for any $I, I^{'} \in \mathcal{I}$, either $u(x, I) \geq u(x, I^{'})$ or $u(x, I^{'}) \geq u(x, I)$. But because $u(\cdot)$ is a utility function representing $\succsim_S$, this implies either that $(x, I) \succsim_S (x^{'}, I)$ or that $(x^{'}, I) \succsim_S (x, I)$, and either that $(x, I) \succsim_S (x, I^{'})$ or that $(x, I^{'}) \succsim_S (x, I)$ (recall Definition 3). Hence, $\succsim_S$ must be complete.

Transitivity. Suppose that $(x, I) \succsim_S (x^{'}, I)$ and $(x^{'}, I) \succsim_S (x^{''}, I)$. Because $u(\cdot)$ represents $\succsim_S$, we must have $u(x, I) \geq u(x^{'}, I)$ and $u(x^{'}, I) \geq u(x^{''}, I)$. Therefore, $u(x, I) \geq u(x^{''}, I)$. Because $u(\cdot)$ represents $\succsim_S$, this implies $(x, I) \succsim_S (x^{''}, I)$. Thus, we have shown that $(x, I) \succsim_S (x^{'}, I)$ and $(x^{'}, I) \succsim_S (x^{''}, I)$ imply $(x, I) \succsim_S (x^{''}, I)$. Analogously, suppose that $(x, I) \succsim_S (x, I^{'})$ and $(x, I^{'}) \succsim_S (x, I^{''})$. Because $u(\cdot)$ represents $\succsim_S$, we must have $u(x, I) \geq u(x, I^{'})$ and $u(x, I^{'}) \geq u(x, I^{''})$. Therefore, $u(x, I) \geq u(x, I^{''})$. Because $u(\cdot)$ represents $\succsim_S$, this implies $(x, I) \succsim_S (x, I^{''})$. Thus, we have shown that $(x, I) \succsim_S (x, I^{'})$ and $(x, I^{'}) \succsim_S (x, I^{''})$ imply $(x, I) \succsim_S (x, I^{''})$, and so transitivity is established. □

A.3. Proof of Proposition 6

For the proof, I follow the strategy of Mas-Colell et al. (1995, pp. 47). First, I assume that the preference relation $\succsim_S$ is monotone (Definition 6) and continuous (Definition 13). Continuity also follows from non-satiation (Definition 7).

Given $\mathcal{I} = \mathbb{R}_+^N$ and $\mathcal{X} = \mathbb{R}_+^M$, let $(\mathcal{X}, \mathcal{I}) = \mathbb{R}_+^L$ with $L = N + M$. Define the locus of vectors in $\mathbb{R}_+^L$ wit all L components equal by

$$Z = (x, I) \in (\mathcal{X}, \mathcal{I})\colon (x_i, I_k) = (x_j, I_l)\ \forall i, j \in M,\ \forall k, l \in N.$$

It will be convenient to let e designate the L-vector whose elements are all equal to 1. Then $\alpha e \in Z$ for all non-negative scalars $\alpha \geq 0$.

Note that for every $(x, I) \in \mathbb{R}_+^L$, monotonicity implies that $(x, I) \succsim_S 0$. Also note that for any $\overline{\alpha}$ such that $\overline{\alpha} e \gg (x, I)$, I have $\overline{\alpha} e \succsim_S (x, I)$. Monotonicity and continuity can then be shown to imply that there is a unique value $\alpha(x, I) \in [0, \overline{\alpha}]$ such that $\alpha(x, I)e \sim_S (x, I)$.

By continuity, the upper and lower contour sets of (x, I) are closed. Hence, the sets $A^+ = \{\alpha \in \mathbb{R}_+ : \alpha e \succsim_S (x, I)\}$ and $A^- = \{\alpha \in \mathbb{R}_+ : (x, I) \succsim_S \alpha e\}$ are non-empty and closed. Note that by completeness of $\succsim_S$ (Definition 2.(i)), $\mathbb{R}_+ \subset (A^+ \cup A^-)$. The non-emptiness and closedness of A^+ and A^-, along with the fact that $\mathbb{R}_+$ is connected, imply that $A^+ \cap A^- \neq \emptyset$. Thus, there exists a scalar α such that $\alpha e \sim_S (x, I)$. Furthermore. by monotonicity, $\alpha_1 e \succ_S \alpha_2 e$ whenever $\alpha_1 > \alpha_2$. Hence, there can be at most one scalar satisfying $\alpha e \sim_S (x, I)$. This scalar is $\alpha(x, I)$.

I now take $\alpha(x, I)$ as my utility function; that is I assign a utility value $U^S(x, I) = \alpha(x, I)$ to every (x, I). I need to check two properties of this function: that it represents the preference $\succsim_S$; [i.e. that $\alpha(x, I) \geq a(x', I') \Leftrightarrow (x, I) \succsim_S (x', I')$] and that it is a continuous function.

That $\alpha(x, I)$ represents preferences follows from its construction. Formally, suppose first that $\alpha(x, I) \geq \alpha(x', I')$. By monotonicity, this implies that $\alpha(x, I)e \succsim_S \alpha(x', I')e$. Since $(x, I) \sim_S \alpha(x, I)e$ and $(x', I') \sim_S \alpha(x', I')e$, I have $(x, I) \succsim_S (x', I')$. Suppose, on the other hand, that $(x, I) \succsim_S (x', I')$. Then $\alpha(x, I)e \sim_S (x, I) \succsim_S (x', I') \sim_S \alpha(x', I')e$;

and so by monotonicity, I must have $\alpha(x, I) \succsim_S \alpha(x^{'}, I^{'})$. Hence, $\alpha(x, I) \geq \alpha(x^{'}, I^{'}) \Leftrightarrow (x, I) \succsim_S (x^{'}, I^{'})$.

I now assume that $\alpha(x, I)$ is a continuous function at all (x, I); that is for any sequence $\{(x^n, I^n)\}_{n=1}^{\infty}$ with $(x, I) = \lim_{n\to\infty}(x^n, I^n)$, I have $\lim_{n\to\infty} \alpha(x^n, I^n) = \alpha(x, I)$. By monotonicity, for any $\epsilon > 0$, $\alpha(x^{'}, I^{'})$ lies in a compact subset of $\mathbb{R}_+$, $[\alpha_0, \alpha_1]$, for all $(x^{'}, I^{'})$ such that $\|(x^{'}, I^{'}) - (x, I)\| \leq \epsilon$. Since $\{\alpha(x^n, I^n)\}_{n=1}^{\infty}$ converges to (x, I), there exists an N such that $\alpha(x^n, I^n)$ lies in this compact set for all $n > N$. Every infinite sequence in a compact set has a convergent sequence and hence also $\{\alpha(x^n, I^n)\}_{n=1}^{\infty}$, must have a convergent subsequence (Bolzano-Weierstrass theorem, Mas-Colell et al., 1995, pp. 943).

What remains is to establish that all convergent subsequences of $\{\alpha(x^n, I^n)\}_{n=1}^{\infty}$ converge to $\alpha(x, I)$. To see this, suppose otherwise: that there is some strictly increasing function $m(\cdot)$ that assigns to each positive integer n a positive integer $m(n)$ and for which the subsequence $\left\{\alpha\left(x^{m(n)}, I^{m(n)}\right)_{n=1}^{\infty}\right\}$ converges to $\alpha^{'} \neq \alpha(x, I)$. I first show that $\alpha^{'} > \alpha(x, I)$ leads to a contradiction. To begin, note that monotonicity would then imply that $\alpha^{'}e \succ_S \alpha(x, I)e$. Now, let $\hat{\alpha} = \frac{1}{2}\left[\alpha^{'} + \alpha(x, I)\right]$. The point $\hat{\alpha}$ is the midpoint on Z between $\alpha^{'}e$ and $\alpha(x, I)e$. By monotonicity, $\hat{\alpha}e \succ_S \alpha(x, I)e$. Now, since $\alpha\left(x^{m(n)}, I^{m(n)}\right) \to \alpha^{'} > \hat{\alpha}$, there exists an $\overline{N}$ such that for all $n > N$, $\alpha\left(x^{m(n)}, I^{m(n)}\right) > \hat{\alpha}$. Hence, for all such n, $\left(x^{m(n)}, I^{m(n)}\right) \sim_S \alpha\left(x^{m(n)}, I^{m(n)}\right) e \succ_S \hat{\alpha}e$ (where the latter relation follows from monotonicity). Because preferences are continuous, this would imply that $(x, I) \succsim_S \hat{\alpha}(x, I)e$. But since $(x, I) \sim_S \alpha(x, I)e$, I get $\alpha(x, I)e \succsim_S \hat{\alpha}e$, which is a contradiction. The argument ruling out $\alpha^{'} < \alpha(x, I)$ is similar. Thus, since all convergent subsequences of $\{\alpha(x^n, I^n)\}_{n=1}^{\infty}$ must converge to $\alpha(x, I)$, I have $\lim_{n\to\infty} \alpha(x^n, I^n) = \alpha(x, I)$, which concludes the proof. □

A.4. Proof of Proposition 7

A continuous function always has a maximum value on any compact set (see Mas-Colell et al., 1995, pp. 943). If $p \gg 0$, then the budget set $B_{p,I} = \left\{x \in \mathbb{R}_+^L : px \leq I\right\}$ is both bounded [for any $\ell = 1, ..., L$, we have $x_\ell \leq (I/p_\ell)$ for all $x \in B_{p,I}$] and closed. Therefore, $B_{p,I}$ is a compact set and the utility maximisation problem has a solution. □

A.5. Proof of Proposition 8

With $\sigma = 0$, the consumer problem collapses to

$$\max_{x,l,g} U(x,l,g) = x + \ln(l) + \ln(g)$$
$$\text{s.t.} \quad (1-t)(1-l)\omega + \tau = x + g.$$

Optimisation gives us the indirect utility

$$V(\omega,t,\tau) = \underbrace{(1-t)\omega + \tau - 2}_{x^*} + \ln\left(\underbrace{\frac{1}{(1-t)\omega}}_{l^*}\right) + \ln(\underbrace{1}_{g^*}).$$

Knowing the consumer response, the social planner sets the optimal policy (t,τ), given her budget constraint $\tau = (1-l)t\omega$. Since $\sigma = 0$, i does not condition her decision regarding the consumption of g on τ and the available policy cannot increase the consumption of g. Therefore, the social planner maximises solely i's indirect utility $V(\tau^*(t))$. Hence, the social planner's problem is

$$\begin{aligned}
\max_t V(\tau^*(t)) &= (1-t)\omega + \left(1 - \frac{1}{(1-t)\omega}\right)t\omega - 2 + \ln\left(\frac{1}{(1-t)\omega}\right) \\
&= \omega - t\omega + t\omega - \frac{t\omega}{(1-t)\omega} - 2 + \ln(1) - \ln(1-t) - \ln(\omega) \\
&= \omega - \frac{t\omega}{(1-t)\omega} - 2 + \ln(1-t) - \ln(\omega).
\end{aligned}$$

With the help of the first order condition, we solve for t^*.

$$\begin{aligned}
\frac{\partial V}{\partial t} = -\frac{(1-t)\omega^2 + t\omega^2}{(1-t)^2\omega^2} + \frac{1}{1-t} &\overset{!}{=} 0 \\
\Leftrightarrow \frac{1}{1-t} &= \frac{\omega^2}{(1-t)^2\omega^2} \\
\Leftrightarrow 1 &= \frac{1}{1-t} \\
\Leftrightarrow 1-t &= 1 \\
\Leftrightarrow t^* &= 0.
\end{aligned}$$

Since, $\frac{\partial^2 V}{\partial t^2} = \frac{2t^2-2t-1}{(1-t)^4}$ is negative for $t = 0$, no governmental intervention is optimal if $\sigma = 0$. $\square$

A.6. Proof of Lemma 1

$$t^*(\omega \leq \underline{\omega}) = 0 \text{ and } t^*(\omega > \underline{\omega}) \geq 0, \text{ with } \underline{\omega} = \frac{1}{(1+\sigma)}. \tag{A.1}$$

Proof. Since $l \in (0,1)$ and $l^* = \frac{1}{\omega(1+\sigma)(1-t)}$, $t^*(\omega \leq \underline{\omega}) = 0$ with $\underline{\omega} = \frac{1}{(1+\sigma)}$.

For $\omega > \underline{\omega}$, $t^* \geq 0$:

$$\begin{aligned}
\tau^* = (1-l^*)t\omega \overset{(I.5)}{=} \omega t - \frac{t}{(1+\sigma)(1-t)} &\geq 0 \\
\Leftrightarrow \omega t &\geq \frac{t}{(1+\sigma)(1-t)} \\
\Leftrightarrow \omega &\geq \frac{1}{(1+\sigma)(1-t)} \\
\Leftrightarrow t &\leq 1 - \frac{1}{(1+\sigma)\omega} = t_{\tau^* \geq 0}.
\end{aligned} \tag{A.2}$$

Following Equations (A.2) and (A.3), for $\omega > \frac{1}{(1+\sigma)}$, $\bar{t} < t_{\tau^* \geq 0}$:

$$\begin{aligned}
\bar{t} &< t_{\tau^*=0} \\
1 - \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}} &< 1 - \frac{1}{(1+\sigma)\omega} \\
\Leftrightarrow \frac{1}{(1+\sigma)\omega} &< \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}} \\
\Leftrightarrow \frac{1}{(1+\sigma)^2\omega^2} &< \frac{1}{(1+\sigma)\omega} \\
\Leftrightarrow \frac{1}{(1+\sigma)\omega} &< 1 \\
\Leftrightarrow \frac{1}{(1+\sigma)} &< \omega.
\end{aligned}$$

$\square$

A.7. Proof of Lemma 2

$$\bar{t} = 1 - \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}}. \tag{A.3}$$

Proof. With

$$\tau^* = (1-l^*)t\omega \overset{(I.5)}{=} \omega t - \frac{t}{(1+\sigma)(1-t)} = \frac{(1+\sigma)(1-t)\omega t - t}{(1+\sigma)(1-t)}, \tag{A.4}$$

$$\begin{aligned}
\frac{\partial \tau^*(t)}{\partial t} =& \frac{\partial}{\partial t}\left(\omega t - \frac{t}{(1+\sigma)(1-t)}\right) \\
=& \omega - \frac{1}{(1+\sigma)(1-t)^2} = \\
=& \frac{(1+\sigma)(1-t)^2\omega - 1}{(1+\sigma)(1-t)^2} \overset{!}{=} 0 \\
\Leftrightarrow (1-t)^2 =& \frac{1}{(1+\sigma)\omega} \\
\Leftrightarrow (1-t) =& \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}} \\
\Leftrightarrow \bar{t} =& 1 - \left(\frac{1}{(1+\sigma)\omega}\right)^{\frac{1}{2}}.
\end{aligned} \tag{A.5}$$

Since

$$\frac{\partial^2 \tau^*(t)}{\partial t^2} = -\frac{2}{(1+\sigma)(1-t)^3} < 0, \tag{A.6}$$

$\bar{t}$ constitutes a maximum. □

A.8. Proof of Proposition 9

First, I show that if g does not exert any externality on others or, alternatively, the social planner does not put any weight on the utility of others, $\epsilon = 0$, then $t^*(0) \geq 0$.

If $\epsilon = 0$, then the social planner maximises solely i's indirect utility. Hence,

$$\begin{aligned}\max_t V(\tau^*(t)) =& \frac{\omega - \sigma + \tau^*(t) + \omega\sigma - \omega t - \sigma^2\tau^*(t) - \omega\sigma t - 2}{1+\sigma} + \\ &+ \ln\left(\frac{1}{\omega(1+\sigma)(1-t)}\right) + \\ &+ (1+\sigma\tau^*(t))\ln(1+\sigma\tau^*(t)) + \\ &+ \frac{\omega\sigma\,(1+\sigma)\,(1-t) - \sigma}{(1+\sigma)}.\end{aligned}$$

This can be simplified to

$$\begin{aligned}\max_t V(\tau^*(t)) =& \omega + \tau^*(t) + \ln(1+\sigma\tau^*(t)) - \ln(1+\sigma) - \ln(1-t) - \\ &- \ln(\omega) + \omega\sigma - \omega t - \sigma\tau^*(t) + \sigma\tau^*(t)\ln(1+\sigma\tau^*(t)) - \omega\sigma t - 2.\end{aligned}$$

Since Proposition 8 shows that $t = 0$ if $\sigma = 0$, it is sufficient to show that $\frac{\partial t}{\partial \sigma} > 0$.

Since in the optimum

$$\frac{\partial V(\tau^*(t))}{\partial t} = 0,$$

the implicit differential is defined by

$$\frac{dt}{d\sigma} = -\frac{\frac{\partial^2 V(\tau^*(t))}{\partial t \partial \sigma}}{\frac{\partial^2 V(\tau^*(t))}{\partial t^2}} > 0.$$

The denominator is negative due to the second-order condition of the consumer, $\frac{\partial^2 V(\tau^*(t))}{\partial t^2} < 0$.

As long as t remains below $\bar{t}$, the enumerator is positive.

Hence $\frac{\partial^2 V(\tau^*(t))}{\partial t \partial \sigma} > 0 \quad \forall t < \bar{t}$:

$$\begin{aligned}
\frac{\partial V(\tau^*(t))}{\partial t} =& \frac{\partial \tau^*(t)}{\partial t} + \frac{\sigma}{1+\sigma\tau^*(t)}\frac{\partial \tau^*(t)}{\partial t} + \frac{1}{1-t} - \omega - \sigma\frac{\partial \tau^*(t)}{\partial t} + \\
&+ \sigma\frac{\partial \tau^*(t)}{\partial t}\ln(1+\sigma\tau^*(t)) + \sigma\tau^*(t)\frac{\sigma}{1+\sigma\tau^*(t)}\frac{\partial \tau^*(t)}{\partial t} - \omega\sigma \\
=& \frac{\partial \tau^*(t)}{\partial t}\left(1 + \frac{\sigma}{1+\sigma\tau^*(t)} - \sigma + \sigma\ln(1+\sigma\tau^*(t)) + \frac{\sigma^2\tau^*(t)}{1+\sigma\tau^*(t)}\right) + \\
&+ \frac{1}{1-t} - \omega - \omega\sigma \\
=& \frac{\partial \tau^*(t)}{\partial t}\left(1 + \frac{\sigma(1+\sigma\tau^*(t))}{1+\sigma\tau^*(t)} - \sigma + \sigma\ln(1+\sigma\tau^*(t))\right) + \\
&+ \frac{1}{1-t} - \omega - \omega\sigma = \\
=& \frac{\partial \tau^*(t)}{\partial t}\left(1 + \sigma\ln(1+\sigma\tau^*(t))\right) + \frac{1}{1-t} - \omega - \omega\sigma \stackrel{!}{=} 0.
\end{aligned} \tag{A.7}$$

$$\begin{aligned}
\Leftrightarrow 1 + \sigma\ln(1+\sigma\tau^*(t)) =& \frac{(1+\sigma)\omega - \frac{1}{1-t}}{\frac{\partial \tau^*(t)}{\partial t}} \stackrel{(A.5)}{=} \frac{\frac{(1+\sigma)(1-t)\omega - 1}{(1-t)}}{\frac{(1+\sigma)(1-t)^2\omega - 1}{(1+\sigma)(1-t)^2}} = \\
=& \frac{(1+\sigma)(1-t)((1+\sigma)(1-t)\omega - 1)}{(1+\sigma)(1-t)^2\omega - 1}.
\end{aligned} \tag{A.8}$$

With

$$\frac{\partial}{\partial \sigma}\left[1 + \sigma\ln(1+\sigma\tau^*(t))\right] = \frac{\sigma}{(1+\sigma\tau^*(t))}\left(\tau^*(t) + \sigma\frac{\partial \tau^*(t)}{\partial \sigma}\right) + \ln(1+\sigma\tau^*(t)), \tag{A.9}$$

and

$$\frac{\partial^2 \tau^*(t)}{\partial t \partial \sigma} = \frac{1}{(1+\sigma)^2(1-t)^2}, \tag{A.10}$$

$$\begin{aligned}
\frac{\partial^2 V(\tau^*(t))}{\partial t \partial \sigma} &= \frac{\partial^2 \tau^*(t)}{\partial t \partial \sigma}(1+\sigma\ln(1+\sigma\tau^*(t)))+ \\
&+ \frac{\partial \tau^*(t)}{\partial t}\left(\frac{\sigma}{(1+\sigma\tau^*(t))}\left(\tau^*(t)+\sigma\frac{\partial \tau^*(t)}{\partial \sigma}\right)+\ln(1+\sigma\tau^*(t))\right)-\omega = \\
&\overset{(A.5,A.8,A.9,A.10)}{=} \frac{1}{(1+\sigma)^2(1-t)^2}\cdot\frac{(1+\sigma)(1-t)((1+\sigma)(1-t)\omega-1)}{(1+\sigma)(1-t)^2\omega-1}+ \\
&+ \frac{(1+\sigma)(1-t)^2\omega-1}{(1+\sigma)(1-t)^2}\left(\frac{\sigma\tau^*(t)+\sigma^2\frac{\partial\tau^*(t)}{\partial\sigma}}{(1+\sigma\tau^*(t))}+\right. \\
&\left.+\frac{1}{\sigma}(1+\sigma\ln(1+\sigma\tau^*(t)))-\frac{1}{\sigma}\right)-\omega = \\
&= \frac{\sigma(1+\sigma)(1-t)^3(1+\sigma\tau^*(t))((1+\sigma)(1-t)\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ \qquad \text{(A.11)} \\
&+ \frac{\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)\left(\sigma\tau^*(t)+\sigma^2\frac{\partial\tau^*(t)}{\partial\sigma}\right)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ \\
&+ \frac{(1+\sigma)^2(1-t)^3(1+\sigma\tau^*(t))((1+\sigma)(1-t)\omega-1)((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}- \qquad \text{(A.12)} \\
&- \frac{(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)^2}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}- \qquad \text{(A.13)} \\
&- \frac{\sigma\omega(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}. \qquad \text{(A.14)}
\end{aligned}$$

By multiplying $(1+\sigma)(1-t)\omega-1)$ with $(1-t)$ and reducing the corresponding exponent in Line (A.11) and Line (A.12), and then expanding t, they can be rewritten as

$$\begin{aligned}
\text{Line }(A.11) &= \frac{\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1+t)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)} = \\
&= \frac{\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ \qquad \text{(A.15)} \\
&+ \frac{t\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}
\end{aligned}$$

and

$$\begin{aligned}
\text{Line }(A.12) &= \frac{(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1+t)((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)} = \\
&= \frac{(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ \\
&+ \frac{t(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)} = \\
&= \frac{(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)^2}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ \qquad \text{(A.16)} \\
&+ \frac{t(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}.
\end{aligned}$$

As $(1+\sigma)^2 = 1+\sigma+\sigma(1+\sigma)$, expanding $(1+\sigma)$ in Line (A.16) gives

$$\begin{aligned}\text{Line }(A.12) =& \frac{(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)^2}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ && \text{(A.17)}\\ &+\frac{\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)^2}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+ && \text{(A.18)}\\ &+\frac{t(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}.\end{aligned}$$

As a result, Line (A.13) and (A.17) cancel out. Line (A.14) can be cancelled out by combining Lines (A.15) and (A.18) and factoring out $(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)$:

$$\frac{(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}\cdot \\ \cdot\left[\underbrace{\sigma\omega(1+\sigma)(1-t)^2-\sigma}_{(A.18)}\underbrace{+\sigma}_{(A.15)}\underbrace{-\sigma\omega(1+\sigma)(1-t)^2}_{(A.14)}\right]=0.$$

Hence, it remains

$$\begin{aligned}\frac{\partial^2 V(\tau^*(t))}{\partial t\partial\sigma} =& \frac{t\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+\\ &+\frac{\sigma(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)\left(\sigma\tau^*(t)+\sigma^2\frac{\partial\tau^*(t)}{\partial\sigma}\right)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}+\\ &+\frac{t(1+\sigma)^2(1-t)^2(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}{\sigma(1+\sigma)^2(1-t)^4(1+\sigma\tau^*(t))((1+\sigma)(1-t)^2\omega-1)}.\end{aligned}$$

One can factor out and cancel $(1+\sigma)(1-t)^2(1+\sigma\tau^*(t))$ and then factor out $(1+\sigma)((1+\sigma)(1-t)^2\omega-1)$:

$$\frac{\partial^2 V(\tau^*(t))}{\partial t\partial\sigma} = \frac{((1+\sigma)(1-t)^2\omega-1)\left[\sigma\left(\sigma\tau^*(t)+\sigma^2\frac{\partial\tau^*(t)}{\partial\sigma}\right)+t(1+\sigma)\right]+\sigma t}{\sigma(1+\sigma)(1-t)^2((1+\sigma)(1-t)^2\omega-1)} > 0 \quad \forall\omega>\hat{\omega},$$

with

$$\hat{\omega} = \frac{t+\sigma^2\tau^*(t)+\sigma^3\frac{\partial\tau^*(t)}{\partial\sigma}}{(1+\sigma)(1-t)^2\left(t+\sigma t+\sigma^2\tau^*(t)+\sigma^3\frac{\partial\tau^*(t)}{\partial\sigma}\right)}. \tag{A.19}$$

As with $\omega > \frac{1}{(1+\sigma)(1-t)^2} \Leftrightarrow t < \bar{t}$, and $\omega > \frac{1}{(1+\sigma)(1-t)^2} \geq \hat{\omega}$, $\frac{\partial^2 V(\tau^*(t))}{\partial t \partial \sigma} > 0$ if $t < \bar{t}$.

Consequently, as long as t remains below $\bar{t}$, the upper bound for t, the implicit differential is positive. Hence, for $\sigma > 0$, $t^* > 0$.

Now, I will characterise the efficient level of taxation when $\epsilon > 0$. Given that $t \geq 0$ if $\sigma > 0$, I only need to show that $\frac{\partial t}{\partial \epsilon} > 0$.

Let

$$F(t,\epsilon) = \frac{\partial V(\tau^*(t))}{\partial t} + \epsilon \frac{\partial V_{-i}(\tau^*(t))}{\partial t} = 0.$$

$$\frac{dt}{d\epsilon} = -\frac{\frac{\partial F}{\partial \epsilon}}{\frac{\partial F}{\partial t}} = -\left(\frac{\frac{\partial V_{-i}(\tau^*(t))}{\partial t}}{\frac{\partial^2 V(\tau^*(t))}{\partial t^2} + \epsilon \frac{\partial^2 V_{-i}(\tau^*(t))}{\partial t^2}} \right) > 0.$$

The denominator is negative due to the second order condition of the social planner. Hence, $\frac{\partial^2 V(\tau^*(t))}{\partial t^2} + \epsilon \frac{\partial^2 V_{-i}(\tau^*(t))}{\partial t^2} < 0$.

Again, the enumerator is positive as long as t remains below its upper bound, $\bar{t}$. Hence, $\frac{\partial V_{-i}(\tau^*(t))}{\partial t} > 0 \quad \forall t < \bar{t}$:

$$\begin{aligned}
\frac{\partial V_{-i}(\tau^*(t))}{\partial t} &= \frac{\sigma \frac{\partial \tau^*(t)}{\partial t}}{1 + \sigma \tau^*(t)} = \\
&\overset{(A.4,A.5)}{=} \frac{\sigma \left(\frac{(1+\sigma)(1-t)^2 \omega - 1}{(1+\sigma)(1-t)^2} \right)}{1 + \sigma \left(\frac{(1+\sigma)(1-t)\omega t - t}{(1+\sigma)(1-t)} \right)} = \\
&= \frac{(1+\sigma)(1-t)^2 \sigma \omega - \sigma}{(1+\sigma)(1-t)^2 \sigma \omega t + (1+\sigma)(1-t)^2 - (1-t)\sigma t}
\end{aligned}$$

$$\frac{\partial V_{-i}(\tau^*(t))}{\partial t} \begin{cases} > 0 & \text{if } \omega > \frac{1}{(1+\sigma)(1-t)^2} \Leftrightarrow t < \bar{t} \text{ and } \sigma > 0, \\ \leq 0 & \text{if } \frac{t+\sigma-\sigma t-1}{(1+\sigma)(1-t)\sigma t} \leq \omega \leq \frac{1}{(1+\sigma)(1-t)^2} \text{ and } \sigma > 0, \text{ and} \\ > 0 & \text{if } \omega < \frac{t+\sigma-\sigma t-1}{(1+\sigma)(1-t)\sigma t} \leq 0 \text{ and } \sigma > 0. \end{cases}$$

To conclude, if g exerts an externality on others or, alternatively, the social planner puts some weight on the utility of others, $\epsilon > 0$, then $t^*(\epsilon) \geq 0 \quad \forall \epsilon, \sigma > 0$. □

Appendix B.

Appendix to Section II.1

B.1. Playing time as an investment

Table B.1.: Ordinary Least Squares regression of playing time as an investment in players younger than 22, 24, 26, and 28 years.

	Grade			
	(1)	(2)	(3)	(4)
Fraction of minutes played$_{t-1}$	-0.230***	-0.259***	-0.264***	-0.259***
	(0.0334)	(0.0338)	(0.0462)	(0.0544)
U22$_{t-1}$ × Fraction of minutes played$_{t-1}$	-0.0914			
	(0.0638)			
U24$_{t-1}$ × Fraction of minutes played$_{t-1}$		0.0161		
		(0.0341)		
U26$_{t-1}$ × Fraction of minutes played$_{t-1}$			0.0194	
			(0.0432)	
U28$_{t-1}$ × Fraction of minutes played$_{t-1}$				0.00967
				(0.0442)
Grade$_{t-1}$	0.229***	0.230***	0.230***	0.230***
	(0.0281)	(0.0284)	(0.0285)	(0.0286)
Back-up grade$_{t-1}$	0.0113	0.0133	0.0125	0.0123
	(0.0518)	(0.0516)	(0.0524)	(0.0522)
Fee-bound transfer	0.00414	0.00391	0.00348	0.00413
	(0.0231)	(0.0230)	(0.0235)	(0.0227)
Transfer fee (in millions)	-0.00193	-0.00194	-0.00190	-0.00193
	(0.00277)	(0.00269)	(0.00279)	(0.00272)
Loan	-0.0297	-0.0234	-0.0239	-0.0234
	(0.0735)	(0.0730)	(0.0732)	(0.0732)
Market value (in millions)	-0.0108***	-0.0108***	-0.0109***	-0.0108***
	(0.00226)	(0.00236)	(0.00240)	(0.00241)
Age	-0.00782	0.0270	0.0232	0.0207
	(0.0354)	(0.0280)	(0.0246)	(0.0287)
Age squared	0.00000166	-0.000569	-0.000490	-0.000457
	(0.000633)	(0.000512)	(0.000485)	(0.000578)
German (1=German)	-0.0868***	-0.0869***	-0.0872***	-0.0870***
	(0.0182)	(0.0180)	(0.0182)	(0.0181)
Google hits$_{t-1}$ (in thousands)	-0.00456	-0.00442	-0.00434	-0.00450
	(0.00603)	(0.00612)	(0.00613)	(0.00623)
Champions League	-0.0437	-0.0456	-0.0461	-0.0459
	(0.0656)	(0.0669)	(0.0665)	(0.0667)
Europa League	-0.143**	-0.145**	-0.145***	-0.145**
	(0.0383)	(0.0389)	(0.0388)	(0.0388)
Rank$_{t-1}$	-0.0106	-0.0106	-0.0106	-0.0106
	(0.00534)	(0.00535)	(0.00536)	(0.00536)
Constant	3.120***	2.610***	2.655***	2.700***
	(0.550)	(0.492)	(0.462)	(0.490)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.360	0.359	0.359	0.359
Observations	2327	2327	2327	2327

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2.: Second-stage Tobit regression for players younger than 22 years.

	Fraction of potential minutes played	
	Season 2	Season 3
Predicted grade	0.741	-1.320
	(1.062)	(0.847)
Back-up grade$_{t-1}$	0.479*	-1.243
	(0.205)	(1.170)
Fee-bound transfer	0.0493	-0.244
	(0.140)	(0.234)
Transfer fee (in millions)	-0.0129	0.0223
	(0.0221)	(0.0390)
Loan	0.119	
	(0.199)	
Market value (in millions)	0.0663*	-0.0383
	(0.0322)	(0.0545)
Age	-2.857	4.750
	(2.379)	(8.167)
Age squared	0.0751	-0.116
	(0.0622)	(0.204)
German (1=German)	0.296	-0.441
	(0.378)	(0.406)
Google hits$_{t-1}$ (in thousands)	-0.0410	0.194
	(0.0467)	(0.190)
Champions League	0.0155	0.382
	(0.264)	(0.848)
Europa League	0.00127	-0.114
	(0.201)	(0.215)
Rank$_{t-1}$	-0.00865	0.0524
	(0.0162)	(0.0643)
Constant	21.81	-40.06
	(17.95)	(77.23)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Observations	166	55

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: None of the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant ($p = .361$ and $p = .170$).

Table B.3.: Second-stage Tobit regression for players younger than 24 years.

	Fraction of potential minutes played		
	Season 2	Season 3	Season 4
Predicted grade	-2.068	-0.367*	-0.751**
	(2.073)	(0.183)	(0.228)
Back-up grade$_{t-1}$	-0.0603	0.286***	0.00654
	(0.483)	(0.0605)	(0.146)
Fee-bound transfer	-0.0560	0.00586	-0.0801
	(0.151)	(0.0575)	(0.142)
Transfer fee (in millions)	0.0158	-0.00585	0.00914
	(0.0429)	(0.00979)	(0.0360)
Loan	-0.155		
	(0.163)		
Market value (in millions)	-0.0434	0.0116*	0.0104
	(0.0920)	(0.00494)	(0.00743)
Age	-0.345	-0.0197	0.573
	(1.669)	(0.442)	(0.974)
Age squared	0.00767	0.000284	-0.0137
	(0.0394)	(0.0105)	(0.0230)
German (1=German)	-0.467	0.0474	0.0437
	(0.563)	(0.0434)	(0.0980)
Google hits$_{t-1}$ (in thousands)	0.0623	0.00641	0.0228
	(0.0883)	(0.0296)	(0.0389)
Champions League	-0.430	0.0289	-0.0103
	(0.492)	(0.109)	(0.242)
Europa League	-0.506	0.00725	-0.201
	(0.537)	(0.0638)	(0.217)
Rank$_{t-1}$	-0.0257	-0.00957	0.0241
	(0.0346)	(0.00969)	(0.0316)
Constant	13.17	0.787	-4.963
	(24.60)	(4.433)	(10.01)
Position Effects	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes
Observations	308	138	62

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Only in Season 4, the Wald test of exogeneity of the instrumented variable (predicted grade) is significant (Season 2: $p = .380$, Season 3: $p = .657$).

Table B.4.: Second-stage Tobit regression for players younger than 26 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.538*	-0.478***	-0.779*	-0.392***
	(0.673)	(0.112)	(0.338)	(0.100)
Back-up grade$_{t-1}$	-0.104	0.103	0.228	-0.0394
	(0.250)	(0.0744)	(0.152)	(0.112)
Fee-bound transfer	-0.0240	0.00581	0.0476	-0.284***
	(0.0792)	(0.0558)	(0.129)	(0.0740)
Transfer fee (in millions)	0.0162	-0.0101	0.00739	0.0146
	(0.0266)	(0.00618)	(0.0112)	(0.0102)
Loan	-0.0526			
	(0.112)			
Market value (in millions)	-0.0297	0.0132**	0.00644	0.00424
	(0.0384)	(0.00476)	(0.0107)	(0.00386)
Age	-0.341	-0.0566	-0.211	1.125*
	(0.560)	(0.215)	(0.442)	(0.573)
Age squared	0.00788	0.00139	0.00507	-0.0240
	(0.0129)	(0.00480)	(0.00968)	(0.0125)
German (1=German)	-0.229	0.0189	0.0688	-0.0912
	(0.131)	(0.0206)	(0.0726)	(0.0602)
Google hits$_{t-1}$ (in thousands)	0.0113	0.000277	-0.0357	0.0639**
	(0.0341)	(0.0203)	(0.0208)	(0.0248)
Champions League	-0.147	0.113	-0.0790	-0.0400
	(0.142)	(0.104)	(0.118)	(0.225)
Europa League	-0.283	0.0153	-0.191	-0.205
	(0.149)	(0.0613)	(0.106)	(0.110)
Rank$_{t-1}$	-0.0128	0.00370	-0.0155	-0.00913
	(0.0147)	(0.0115)	(0.0114)	(0.0164)
Constant	10.59	2.420	3.760	-10.98
	(8.526)	(2.379)	(5.560)	(6.901)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	455	236	103	68

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: None of the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .056$, Season 3: $p = .109$, Season 4: $p = .231$, Season 5: $p = .720$).

Table B.5.: Second-stage Tobit regression for players younger than 28 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-1.314**	-0.511**	-0.779**	-1.117*
	(0.436)	(0.159)	(0.241)	(0.444)
Back-up grade$_{t-1}$	-0.0191	0.132	0.260**	-0.0512
	(0.133)	(0.0769)	(0.0984)	(0.174)
Fee-bound transfer	-0.0556	-0.0108	0.0125	-0.0602
	(0.0597)	(0.0410)	(0.0710)	(0.104)
Transfer fee (in millions)	0.0122	-0.00354	-0.0154***	0.00264
	(0.0110)	(0.00277)	(0.00413)	(0.00754)
Loan	-0.0711			
	(0.0952)			
Market value (in millions)	-0.0213	0.00772	0.00712	-0.0148
	(0.0174)	(0.00528)	(0.00567)	(0.0112)
Age	-0.144	0.0393	0.351	0.722
	(0.185)	(0.118)	(0.219)	(0.473)
Age squared	0.00334	-0.000769	-0.00715	-0.0159
	(0.00405)	(0.00253)	(0.00463)	(0.00986)
German (1=German)	-0.180*	0.0222	0.0555	-0.166
	(0.0849)	(0.0204)	(0.0567)	(0.132)
Google hits$_{t-1}$ (in thousands)	0.0171	-0.00433	0.0120	0.0853*
	(0.0236)	(0.0146)	(0.0133)	(0.0350)
Champions League	-0.169	0.0508	-0.114	0.195
	(0.128)	(0.114)	(0.106)	(0.265)
Europa League	-0.244*	0.00240	-0.127	-0.0554
	(0.115)	(0.0674)	(0.0667)	(0.0999)
Rank$_{t-1}$	-0.0124	0.000514	-0.0170	0.00790
	(0.0107)	(0.00978)	(0.0125)	(0.0183)
Constant	7.152*	1.183	-2.783	-3.490
	(3.635)	(1.398)	(2.555)	(6.213)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	589	318	152	108

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Only for Season 2 (p = .018), the Wald test of exogeneity of the instrumented variable (predicted grade) is significant (Season 2: p = .225, Season 4: p = .052, and Season 5: p = .074).

Table B.6.: Second-stage Tobit regression for players older than 23 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-0.809***	-0.609***	-0.824***	-0.814*
	(0.161)	(0.122)	(0.237)	(0.355)
Back-up grade$_{t-1}$	-0.00755	0.0724	0.182	0.159
	(0.0609)	(0.0872)	(0.132)	(0.183)
Fee-bound transfer	0.00620	0.00879	0.0400	0.0251
	(0.0519)	(0.0411)	(0.0663)	(0.143)
Transfer fee (in millions)	0.000645	0.00142	-0.0144***	-0.00332
	(0.00388)	(0.00645)	(0.00309)	(0.00910)
Loan	0.0418			
	(0.156)			
Market value (in millions)	0.00180	0.00381	0.00649	-0.0136
	(0.00761)	(0.00486)	(0.00473)	(0.0147)
Age	0.0694	-0.0198	0.176	-0.0549
	(0.0989)	(0.105)	(0.157)	(0.226)
Age squared	-0.00125	0.0000787	-0.00312	0.000796
	(0.00173)	(0.00191)	(0.00270)	(0.00368)
German (1=German)	-0.0342	-0.0872**	0.0208	-0.0226
	(0.0317)	(0.0298)	(0.0399)	(0.128)
Google hits$_{t-1}$ (in thousands)	-0.00966	-0.00983	0.0102	0.0429
	(0.00907)	(0.0121)	(0.0123)	(0.0518)
Champions League	-0.142	0.00480	-0.362*	0.275
	(0.108)	(0.119)	(0.145)	(0.176)
Europa League	-0.151*	-0.0645	-0.217**	-0.00557
	(0.0671)	(0.0340)	(0.0779)	(0.136)
Rank$_{t-1}$	-0.0129*	-0.00000864	-0.0337**	0.00878
	(0.00541)	(0.00501)	(0.0129)	(0.0143)
Constant	2.742	2.365	-0.197	3.458
	(1.759)	(1.530)	(2.366)	(4.745)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	459	311	172	107

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .092$), the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .002$, Season 3: $p = .008$, Season 4: $p = .020$).

Table B.7.: Second-stage Tobit regression for players older than 25 years.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted grade	-0.832***	-0.685**	-1.002**	-0.114
	(0.141)	(0.216)	(0.348)	(0.304)
Back-up grade$_{t-1}$	0.0960	0.186	0.166	0.0343
	(0.0685)	(0.0999)	(0.189)	(0.0615)
Fee-bound transfer	0.00818	-0.0180	0.0146	0.0629
	(0.0605)	(0.0552)	(0.0842)	(0.0588)
Transfer fee (in millions)	0.000311	0.0108	-0.0205***	0.00434*
	(0.00430)	(0.00782)	(0.00523)	(0.00201)
Loan	-0.164			
	(0.203)			
Market value (in millions)	0.00433	-0.00643	0.0116	0.000692
	(0.00422)	(0.00671)	(0.00895)	(0.00908)
Age	-0.158	-0.200	0.495	0.186
	(0.201)	(0.202)	(0.253)	(0.152)
Age squared	0.00244	0.00295	-0.00817	-0.00319
	(0.00337)	(0.00344)	(0.00422)	(0.00245)
German (1=German)	-0.0284	-0.127**	0.00236	0.0689
	(0.0421)	(0.0462)	(0.0547)	(0.0555)
Google hits$_{t-1}$ (in thousands)	-0.0118	0.0188	0.00753	-0.0188
	(0.0110)	(0.0204)	(0.0290)	(0.0354)
Champions League	-0.190	-0.00798	-0.436	0.125
	(0.131)	(0.141)	(0.279)	(0.103)
Europa League	-0.219*	-0.0139	-0.232	0.0860
	(0.0883)	(0.0611)	(0.136)	(0.146)
Rank$_{t-1}$	-0.0169	-0.00145	-0.0369	0.0165
	(0.0103)	(0.00856)	(0.0208)	(0.0118)
Constant	5.958	4.693	-4.559	-2.207
	(3.141)	(2.802)	(4.131)	(1.421)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	312	213	131	81

Standard errors clustered on the team level in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Except for Season 5 ($p = .938$), the Wald tests of exogeneity of the instrumented variable (predicted grade) are significant (Season 2: $p = .000$, Season 3: .035, Season 4: $p = .0.038$).

B.2. Season level

Table B.8.: Second-stage Tobit regression of the fraction of minutes played on predicted disaggregated measures for goalkeepers and defenders.

	Fraction of potential minutes played			
	Season 2	Season 3	Season 4	Season 5
Predicted conceded goals	0.0197***	0.0188***	0.0207	0.00611
	(0.00451)	(0.00415)	(0.0107)	(0.00461)
Predicted assists	-0.0483	-0.0236	-0.0196	0.0737
	(0.137)	(0.0520)	(0.0755)	(0.0685)
Predicted yellow cards	0.0245	0.102	0.0781	0.0199
	(0.0881)	(0.0906)	(0.0974)	(0.0243)
Predicted yellow-red cards	0.178	-1.245	-0.762	-0.300
	(0.410)	(0.646)	(1.999)	(0.827)
Predicted red cards	-0.324	-0.227	0.357	-0.630
	(2.058)	(1.297)	(0.612)	(0.344)
Back-up conceded goals$_{t-1}$	-0.00149	-0.00355	0.00121	-0.0150
	(0.00583)	(0.0160)	(0.0183)	(0.00943)
Back-up assists$_{t-1}$	0.0427	0.0670	0.0527	0.111
	(0.145)	(0.0669)	(0.235)	(0.145)
Back-up yellow cards$_{t-1}$	-0.00515	-0.0101	-0.0543	-0.0211
	(0.0800)	(0.0584)	(0.0701)	(0.0785)
Back-up yellow-red cards$_{t-1}$	0.270	0.150	-0.0133	0.334
	(0.264)	(0.450)	(1.777)	(0.654)
Back-up red cards$_{t-1}$	-0.145	-0.00876	-0.0379	-0.0897
	(0.158)	(0.345)	(0.435)	(0.428)
Fee-bound transfer	0.0192	0.0514	-0.0000407	-0.0633
	(0.0322)	(0.0512)	(0.117)	(0.0955)
Transfer fee (in millions)	-0.0207	-0.00585	-0.00399	0.00612
	(0.0131)	(0.0110)	(0.00756)	(0.00729)
Loan	0.0196			
	(0.238)			
Market value (in millions)	0.0389*	0.0167	0.0124	0.0229
	(0.0177)	(0.0121)	(0.0147)	(0.0152)
Age	-0.0312	-0.0915	-0.0308	0.0838
	(0.109)	(0.0527)	(0.143)	(0.109)
Age squared	0.000661	0.00145	0.000539	-0.00120
	(0.00218)	(0.000909)	(0.00258)	(0.00179)
German (1=German)	-0.0129	-0.0725	0.00595	0.0382
	(0.139)	(0.0648)	(0.168)	(0.107)
Google hits$_{t-1}$ (in thousands)	0.00828	-0.0101	-0.0354	-0.0266
	(0.0265)	(0.0505)	(0.0325)	(0.0335)
Champions League	0.124	-0.152	0.0987	-0.441**
	(0.310)	(0.198)	(0.257)	(0.155)
Europa League	0.105	-0.0898	-0.0768	-0.193
	(0.221)	(0.112)	(0.223)	(0.141)
Rank$_{t-1}$	0.00985	-0.0146	0.00851	-0.0180*
	(0.0225)	(0.0191)	(0.0229)	(0.00777)
Constant	0.706	1.955	0.525	-0.608
	(2.623)	(1.348)	(2.193)	(1.550)
Position Effects	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes
Observations	421	246	145	92

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: All Wald tests of exogeneity of the instrumented variable (predicted conceded goals, assists, and cards) are significant.

B.3. Match level

Table B.9.: Ordinary Least Squares regression of minutes played per match using eight lagged variables.

	Minutes played	
Match grade$_{t-1}$ if graded	-4.921***	(0.494)
Match grade$_{t-2}$ if graded	-2.197***	(0.228)
Match grade$_{t-3}$ if graded	-1.310***	(0.106)
Match grade$_{t-4}$ if graded	-0.909***	(0.151)
Match grade$_{t-5}$ if graded	-0.956***	(0.139)
Match grade$_{t-6}$ if graded	-0.345*	(0.132)
Match grade$_{t-7}$ if graded	-0.554**	(0.185)
Match grade$_{t-8}$ if graded	-0.541**	(0.180)
Match graded$_{t-1}$	43.05***	(2.919)
Match graded$_{t-2}$	17.81***	(1.233)
Match graded$_{t-3}$	9.777***	(0.528)
Match graded$_{t-4}$	7.444***	(0.615)
Match graded$_{t-5}$	6.980***	(0.782)
Match graded$_{t-6}$	4.754***	(0.533)
Match graded$_{t-7}$	5.986***	(0.892)
Match graded$_{t-8}$	6.846***	(0.572)
Match played$_{t-1}$	8.460***	(0.490)
Match played$_{t-2}$	3.182***	(0.563)
Match played$_{t-3}$	1.912***	(0.402)
Match played$_{t-4}$	0.0780	(0.486)
Match played$_{t-5}$	0.0665	(0.405)
Match played$_{t-6}$	-0.687*	(0.337)
Match played$_{t-7}$	-0.539	(0.473)
Match played$_{t-8}$	0.309	(0.427)
Match backup grade$_{t-1}$ if graded	1.091***	(0.286)
Match backup grade$_{t-2}$ if graded	0.218	(0.162)
Match backup grade$_{t-3}$ if graded	0.183	(0.161)
Match backup grade$_{t-4}$ if graded	-0.0640	(0.138)
Match backup grade$_{t-5}$ if graded	0.0994	(0.155)
Fee-bound transfer	0.553	(0.644)
Transfer fee (in millions)	0.0824	(0.0430)
Loan	-0.403	(1.052)
Market value (in millions)	0.399**	(0.144)
Age	1.455**	(0.417)
Age squared	-0.0254**	(0.00815)
German (1=German)	0.521	(0.361)
Google hits previous season (in thousands)	-0.151	(0.168)
Hiring coach	0.0899	(0.340)
Tenure in team	0.0302**	(0.00876)
Tenure in team squared	-0.0000618	(0.0000322)
Number of players in team	0.0702	(0.0376)
Champions League	0.0467	(0.588)
Europa League	-0.0495	(0.421)
Rank difference	0.0877***	(0.0132)
Rank difference squared	0.00238	(0.00151)
Match day	0.181***	(0.0404)
Match day squared	-0.00379***	(0.000968)
Constant	-26.70***	(5.451)
Position Effects	Yes	
Team Effects	Yes	
Season Effects	Yes	
Adjusted R^2	0.531	
Observations	77563	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.10.: Second-stage Tobit regression of minutes played per match using lagged grades of five matches, interacting the transfer fee variables with the player's tenure in the team.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-120.2***	
	(11.13)	
Fee-bound transfer	8.061	0.0171
	(5.603)	(0.0296)
Transfer fee (in millions)	1.086**	0.00373
	(0.351)	(0.00212)
Fee-bound transfer × Tenure in team	-0.0682	-0.000178
	(0.0534)	(0.000310)
Transfer fee (in millions) × Tenure in team	-0.0110***	-0.0000562*
	(0.00328)	(0.0000257)
Back-up match grade$_{t-1}$	-2.971***	-0.0254***
	(0.845)	(0.00510)
Loan	-9.129	-0.0675
	(8.667)	(0.0569)
Market value (in millions)	0.0189	-0.0109***
	(0.426)	(0.00178)
Age	9.047*	0.0369
	(4.343)	(0.0226)
Age squared	-0.179*	-0.000830
	(0.0838)	(0.000425)
German (1=German)	-4.079	-0.0596***
	(2.734)	(0.0153)
Google hits previous season (in thousands)	0.887	0.00586
	(1.030)	(0.00508)
Hiring coach	-2.546	-0.0318*
	(1.722)	(0.0147)
Tenure in team	0.155**	-0.000385
	(0.0523)	(0.000372)
Tenure in team squared	-0.000271	0.00000100
	(0.000170)	(0.000000788)
Number of players in team	1.305**	0.00879**
	(0.457)	(0.00296)
Champions League	-4.272	-0.00665
	(6.342)	(0.0364)
Europa League	-10.94**	-0.0762**
	(3.422)	(0.0247)
Rank difference	0.889***	0.00537***
	(0.110)	(0.000605)
Rank difference squared	-0.00369	-0.0000577
	(0.00930)	(0.0000378)
Match day	0.389*	-0.00126
	(0.178)	(0.000999)
Match day squared	-0.0133**	0.00000831
	(0.00474)	(0.0000271)
Constant	289.6***	3.540***
	(71.86)	(0.314)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	71952	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The player's tenure in team is measured in matches. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table B.11.: Second-stage Tobit regression of minutes played per match on a seasonal level, interacting the transfer fee variables with the player's tenure in the team.

	Minutes per match				
	Season 1	Season 2	Season 3	Season 4	Season 5
Predicted grade	-114.7***	-97.09***	-88.07***	-82.34***	-94.25***
	(10.07)	(12.23)	(12.66)	(11.20)	(16.43)
Back-up match grade$_{t-1}$	-1.530	-0.797	-3.324*	-4.127*	-9.844**
	(1.080)	(1.060)	(1.340)	(1.889)	(3.080)
Fee-bound transfer	5.125	-5.092	-8.395	-3.861	44.11*
	(4.463)	(7.769)	(12.75)	(29.12)	(17.32)
Transfer fee (in millions)	0.441	2.336*	-1.138	8.896	11.51**
	(0.440)	(0.940)	(1.543)	(4.856)	(4.379)
Fee-bound transfer × Tenure in team	0.0311	0.143	0.178	0.0436	-0.304*
	(0.207)	(0.138)	(0.156)	(0.268)	(0.144)
Transfer fee (in millions) × Tenure in team	0.00255	-0.0340	0.00831	-0.0694	-0.0707*
	(0.0202)	(0.0175)	(0.0203)	(0.0390)	(0.0295)
Loan	2.954	-4.768			
	(4.072)	(6.230)			
Market value (in millions)	0.0598	-0.0779	-0.0629	0.813	-0.784
	(0.443)	(0.746)	(0.541)	(0.789)	(0.422)
Age	7.107	0.876	6.430	17.83*	-12.60
	(4.628)	(5.555)	(5.968)	(7.912)	(7.703)
Age squared	-0.120	-0.0198	-0.130	-0.331*	0.173
	(0.0902)	(0.104)	(0.118)	(0.153)	(0.134)
German (1=German)	-4.084	-6.396*	-1.676	0.669	-1.151
	(2.840)	(2.835)	(3.518)	(3.699)	(4.945)
Google hits current season (in thousands)	-0.916				
	(0.688)				
Google hits previous season (in thousands)		0.127	1.424	-2.826	3.882
		(1.081)	(2.345)	(1.870)	(2.129)
Hiring coach	-4.581	-0.616	-5.020	-2.107	18.09***
	(2.656)	(2.288)	(4.671)	(6.477)	(4.966)
Tenure in team	-2.449***	0.292	-0.0756	0.421	0.0966
	(0.671)	(0.612)	(0.587)	(0.595)	(0.492)
Tenure in team squared	0.0490***	-0.00178	-0.000418	-0.00183	0.00113
	(0.0148)	(0.00665)	(0.00426)	(0.00287)	(0.00229)
Number of players in team	1.007	0.734	0.998	2.108	0.0928
	(0.578)	(0.580)	(0.574)	(1.317)	(0.641)
Champions League	-0.693	0.999	-4.526	-10.29	-5.726
	(6.658)	(8.167)	(9.265)	(7.963)	(9.484)
Europa League	-7.852	-8.143	-2.158	-13.64	-24.77***
	(4.228)	(5.008)	(3.283)	(7.910)	(6.353)
Rank difference	0.851***	0.731***	0.284*	0.949***	0.370
	(0.158)	(0.133)	(0.129)	(0.218)	(0.316)
Rank difference squared	-0.00725	0.00766	-0.00408	-0.00383	-0.00177
	(0.0101)	(0.0157)	(0.0141)	(0.0211)	(0.0257)
Match day	1.868**	-0.0211	0.512	0.725	0.596
	(0.628)	(0.408)	(0.397)	(0.527)	(0.819)
Match day squared	-0.0404**	-0.000369	-0.0123	-0.0180	-0.0237
	(0.0141)	(0.0104)	(0.0129)	(0.0126)	(0.0208)
Constant	324.7***	327.8***	166.4*	-30.78	552.6***
	(63.25)	(89.24)	(84.80)	(105.2)	(145.0)
Position Effects	Yes	Yes	Yes	Yes	Yes
Team Effects	Yes	Yes	Yes	Yes	Yes
Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	32449	23954	15092	9614	6746

Standard errors clustered on the team level in parentheses
Grade instrumented with grades of previous 20 (5 in the first season) match days.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The player's tenure in team is measured in matches. As in the first season, there are only a few players for whom I have a figure on their Google hits in the previous season, I use the Google hits for the current season in Season 1. All Wald tests of exogeneity of the instrumented variable (predicted match grade) are significant.

Table B.12.: Second-stage Tobit regression of minutes played per match on relative transfer fees.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-85.87***	
	(9.166)	
Relative transfer fee	29.35	-0.230
	(19.69)	(0.118)
Back-up match grade$_{t-1}$	-3.370***	-0.0320***
	(0.736)	(0.00470)
Loan	-3.530	-0.0434
	(5.541)	(0.0513)
Market value (in millions)	0.166	-0.00540***
	(0.322)	(0.00112)
Age	7.616*	0.0286
	(3.683)	(0.0209)
Age squared	-0.155*	-0.000656
	(0.0711)	(0.000399)
German (1=German)	-2.151	-0.0493***
	(2.300)	(0.0143)
Google hits previous season (in thousands)	-0.0319	0.00157
	(0.820)	(0.00384)
Hiring coach	-1.134	-0.0335**
	(1.356)	(0.0119)
Tenure in team	0.0686	-0.000478
	(0.0380)	(0.000271)
Tenure in team squared	-0.000153	0.000000845
	(0.000133)	(0.000000822)
Number of players in team	0.978**	0.00548*
	(0.372)	(0.00238)
Champions League	-2.345	0.0225
	(4.830)	(0.0313)
Europa League	-7.429**	-0.0516*
	(2.560)	(0.0201)
Rank difference	0.649***	0.00416***
	(0.0801)	(0.000622)
Rank difference squared	-0.000414	-0.0000602
	(0.00796)	(0.0000335)
Match day	0.439**	-0.000534
	(0.149)	(0.00109)
Match day squared	-0.0123**	-0.00000847
	(0.00386)	(0.0000282)
Constant	179.7**	3.772***
	(57.54)	(0.300)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68067	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Table B.13.: Second-stage Tobit regression of minutes played per match, interacting the transfer fee variables with the coach's age.

	Second stage Minutes per match	First stage Predicted grade
Predicted grade	-85.73***	
	(9.187)	
Back-up match grade$_{t-1}$	-3.407***	-0.0321***
	(0.740)	(0.00476)
Fee-bound transfer	3.028	0.0534
	(12.35)	(0.0883)
Fee-bound transfer × Age in days of coach at match day	-0.000114	-0.00000289
	(0.000709)	(0.00000463)
Transfer fee (in millions)	0.497	-0.00248
	(0.464)	(0.00706)
Transfer fee (in millions) × Age in days of coach at match day	-0.0000189	-4.05e-08
	(0.0000246)	(0.000000311)
Loan	-3.976	-0.0446
	(5.548)	(0.0534)
Market value (in millions)	0.177	-0.00503***
	(0.303)	(0.00129)
Age	7.675*	0.0260
	(3.708)	(0.0215)
Age squared	-0.156*	-0.000602
	(0.0713)	(0.000408)
German (1=German)	-2.383	-0.0479***
	(2.368)	(0.0145)
Google hits previous season (in thousands)	-0.126	0.00324
	(0.850)	(0.00372)
Hiring coach	-1.102	-0.0313**
	(1.279)	(0.0121)
Tenure in team	0.0660	-0.000457
	(0.0378)	(0.000280)
Tenure in team squared	-0.000144	0.000000737
	(0.000135)	(0.000000868)
Number of players in team	0.952*	0.00559*
	(0.374)	(0.00238)
Champions League	-2.727	0.0241
	(4.737)	(0.0303)
Europa League	-7.591**	-0.0500*
	(2.578)	(0.0195)
Rank difference	0.648***	0.00419***
	(0.0801)	(0.000640)
Rank difference squared	-0.000406	-0.0000575
	(0.00787)	(0.0000345)
Match day	0.442**	-0.000528
	(0.149)	(0.00110)
Match day squared	-0.0123**	-0.00000823
	(0.00388)	(0.0000287)
Constant	179.8**	3.786***
	(58.10)	(0.312)
Position Effects	Yes	Yes
Team Effects	Yes	Yes
Season Effects	Yes	Yes
Grades of previous 20 match days	No	Yes
Observations	68007	

Standard errors clustered on the team level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The coach's age is measured in days. The Wald test of exogeneity of the instrumented variable (predicted match grade) is significant.

Appendix C.

DataGorri: A Tool for Automated Data Collection of Tabular Web Content

C.1. Introduction

"The ultimate goal of economic science is to improve the living conditions of people in their everyday lives" (Samuelson and Nordhaus, 1998, p. 7). To realise this goal, it uses theoretical models to derive predictions and analyses data in order to test hypotheses.

In recent decades, the number of empirical studies has grown tremendously. Between 1963 and 2011, the share of empirical articles published in the American Economic Review (AER), Journal of Political Economy (JPE), and Quarterly Journal of Economics (QJE), all of which are top journals, has increased by 34 percent from 47.8 to 63.9 percent. This rise is mainly attributable to the expanding feasibility and popularity of using individually assembled data. Since 1993 in particular, the share of studies using own data instead of publicly provided data has quadrupled (Hamermesh, 2013).

This development coincides with the introduction of the World Wide Web in 1991. The internet has proven to be a primary resource for empirical research, augmenting the amount of available data and lowering the costs of access to it (Edelman, 2012). As of August 2018, Netcraft (2018) counted over 184 million active websites. Many of these provide information that is valuable to economic scholars and can provide further insights to open questions. Some of the available data even is entirely novel and allows new research projects.

However, usually, information on websites is not gathered and presented for scientific use. Also, required data is often provided by many different sources. As a result, a critical lack of structure seems to be the norm (Einav and Levin, 2014a,b). This makes the task of manually compiling online data very time-consuming. Unfortunately, the bulk of software that automates such processes is often too expensive for academic use. Moreover, software must be tailored to specific projects, which further increases costs and decreases scope. Thus, many hours of scholarly work have been used to copy and paste numbers, tables, and texts. Those researchers that are gifted with coding skills may have spent hours creating lines to simplify this job. Yet, in comparison to research data, which is increasingly made public by authors, such code snippets or entire software packages often seem to be kept private and are thus rather difficult to find.

In order to facilitate further research with internet data, we decided to develop and share a software package that might benefit others in their data collection. Here, we introduce DataGorri[1], a free-to-use software that is generically applicable and can collect data from almost all standardised tables on the web.[2]

The software can be used free of charge. However, by accepting the license agreement when downloading DataGorri, the user agrees to cite the corresponding technical paper[3] whenever DataGorri has been used for research purposes (cite ware). The package and documentation can be downloaded from `www.julianhackinger.com/software/datagorri/` and `https://github.com/julhac/datagorri`.

DataGorri is by no means a final product. As only its application can uncover bugs or further potential, anyone is kindly invited to contribute and to send in suggestions for improvement. For this purpose and for problems or questions, please consult the FAQ on the website (`www.julianhackinger.com/software/datagorri/faq/`) or contact the author.

[1]Katagorri = Basque name for squirrel; DataGorri collects data like a squirrel gathers nuts.

[2]Before scraping websites, please ensure that you have the permission to do so.

[3]Hackinger, J. (2018). DataGorri: A Tool for Automated Data Collection of Tabular Web Content. *Netnomics*, 19(1-2):31-41. Please see `https://doi.org/10.1007/s11066-018-9125-2`.

In the following section, we describe how DataGorri works in theory and how it can assist in the data collection process. Subsequently, in Section C.3, we put the theory into practice and use DataGorri to download data on institutions in the RePEc archive. Section C.4 points out advantages and limitations and discusses further possible improvements. Section C.5 concludes.

C.2. DataGorri

DataGorri is an application used to extract data from tables found on websites. It has the ability to run through a list of predefined links and save specified information from tables. Importantly, the respective tables must always be located in the same place of each link and of the same format (the same number of columns; the number of rows is irrelevant). This applies for instance to academic rankings by region (e.g. https://ideas.repec.org/top/top.usa-ma.html), sporting squads and statistics by team, or year (e.g. https://www.transfermarkt.com/1-bundesliga/tabelle/wettbewerb/L1?saison_id=2016), and monthly weather tables (e.g. https://en.tutiempo.net/climate/01-2017/ws-108660.html). At the end of a scraping task, the data is saved to a .csv file format that can be read by common statistics packages.

In order to set up a scraping task, two steps are necessary:

1. Create a page model to define the content of interest.
2. Input links of websites that should be scraped.

C.2.1. The Page Model

The first step is handled by DataGorri's modeler (Figure C.1) which can be found under the tab "MODELER". Here, the user has to input an URL and inspect the website's structure to define the contents which she is interested in. To this end, the modeler displays all tables contained on the respective page. On the first level, it lists mother tables including consecutive number, their headers if available, and a tick box to define whether the table is repetitive or non-repetitive.

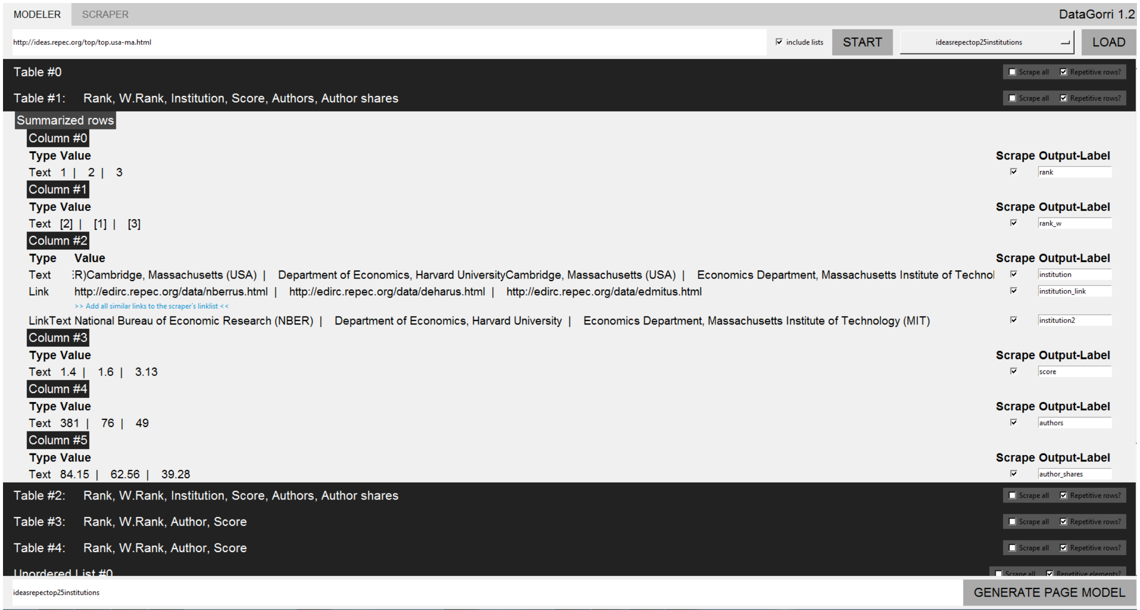


Figure C.1.: The modeler is used to create a page model that is applied to a list of websites.

Repetitive tables (Table C.1) contain information for multiple observations with observations being below one another. In repetitive tables, each column contains information belonging to one variable. Hence, variable names are ordered horizontally on the top. In contrast, non-repetitive tables (Table C.2) usually contain only information on one object or observation. Here, the variable names are ordered vertically on the left. The user must specify whether the table is repetitive or not for the data to be displayed and downloaded correctly.

Table C.1.: Repetitive table.

Object	**Cost**	**Availability**
table	250	yes
chair	50	yes
bed	150	no

Table C.2.: Non-repetitive table.

Object	table
Cost	250
Availability	yes

By clicking the header of each table, the modeler provides more detail on the information contained in the table. Some tables contain so-called child tables (tables within tables, see for example Table C.3 in which the column "Information" contains child tables) which can equally be expanded to show the contained data. The user then simply selects the desired contents of one or more of these tables and, by saving it, creates a page model for this specific page structure. The model can then be used for all similarly structured pages.

Table C.3.: Mother table with child tables.

Object	Cost	Information (child tables)	
		Colour	**Availability**
table	250	black	100
		white	0
		red	70
chair	50	black	80
		white	10
		red	70
bed	150	black	0
		white	0
		red	50

C.2.2. Link List

The second step is collecting one or more URLs that should be scraped with a certain page model. These links should be entered below one another in the "SCRAPER" tab (Figure C.2). To be able to run the same request at a later time, we recommend saving the list of links under a meaningful name.

In order to facilitate the collection of links, DataGorri includes two methods to quickly collect multiple similar URLs. First, this is the link generator at the right hand side of the tab "SCRAPER". Many websites are structured in a way such that a main URL is followed by a count variable that incrementally increases (e.g. page number or year: `www.example.com/data/2016`). By replacing the counter with "{X}" and defining the corresponding range for "X", one can add multiple URLs at once.

The second method can be found in DataGorri's modeler tab. After having loaded a page structure, the modeler displays the option "Add all similar links to the scraper's linklist" whenever it encounters a hyperlink. Once one has found an overview page that includes links to websites that should all be scraped, the second option can be used to easily add several links to the link list.

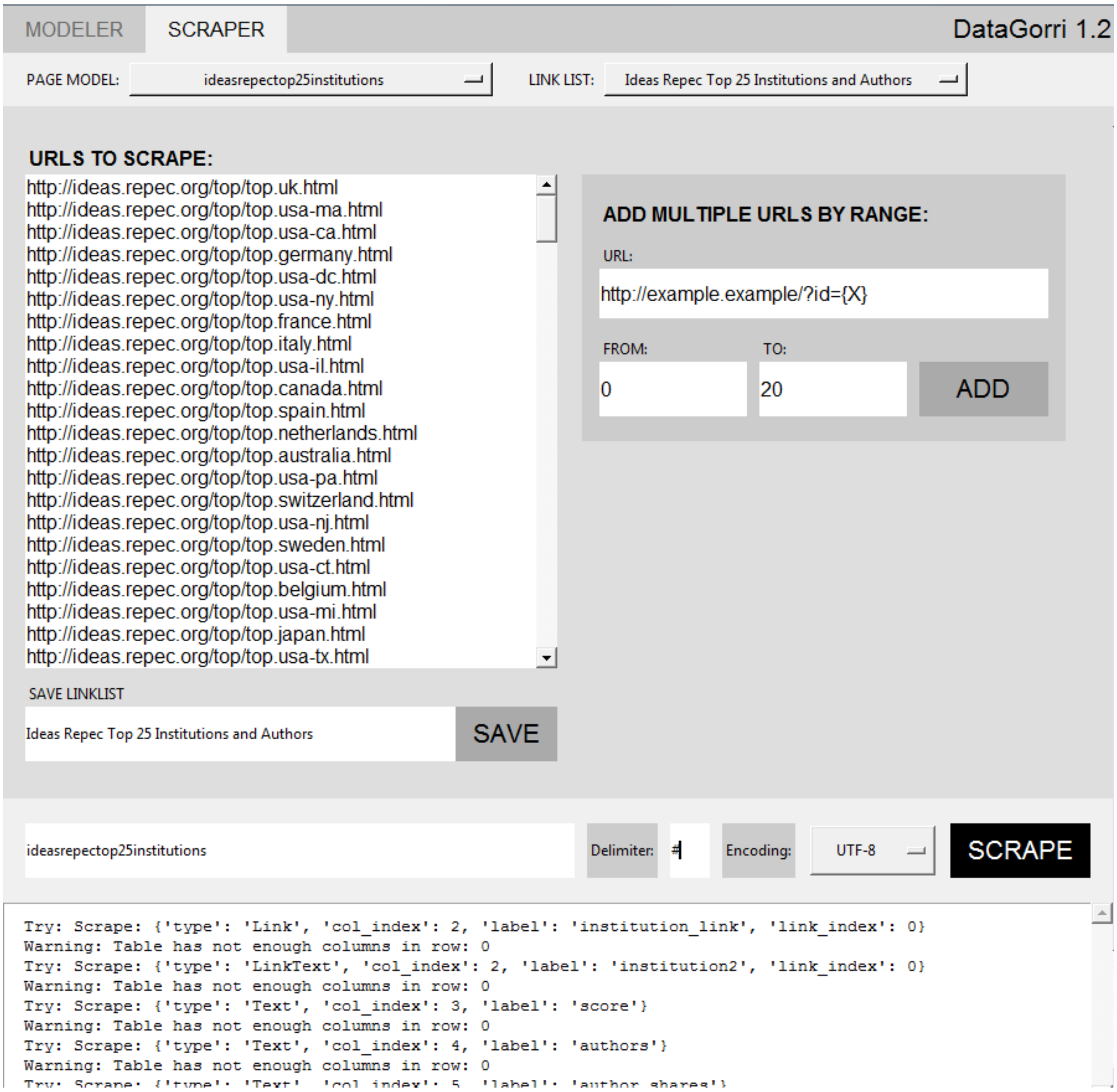


Figure C.2.: In the subsection of the scraper, the user can enter a list of websites that contain formally identical tables which will be scraped.

Ultimately, upon clicking "SCRAPE", DataGorri will go through the selected list of URLs and extract all data located in the predefined cells or positions. After completion, the scraped result is automatically saved to a .csv file format. Please bear in mind that existing files with an identical name are overwritten.

All files (page models, link lists, and result files) are saved in folders on the desktop that are automatically created upon the first execution of DataGorri. The files can also be shared, which facilitates the replication of studies that used DataGorri.

With these basic functions, DataGorri is highly flexible but remains user-friendly and comprehensible even for non-experienced users. For more detailed information on its functionality, please consider the user manual and documentation of DataGorri.

C.3. Application

C.3.1. Research question

So far, we provided the motivation to develop and use DataGorri and described its usage in theory. However, it certainly helps interested readers to see how DataGorri can be applied in practice. For demonstration purposes, we picked an exemplary research question.

We are interested in whether and how the number of authors or academics per institution is correlated with the institution's average research performance. In a broader sense, efficiency and economies of scale in research are frequently discussed topics (Abramo et al., 2012). Wuchty et al. (2007) show that research output benefits from collaborations. A larger institution implies a larger pool of scholars that might have matching research interests. Therefore, it seems reasonable that larger institutions facilitate conducting projects in teams and finding co-authors. Moreover, a better match in research interests or a higher number of matches should also increase the likelihood to receive valuable input from colleagues. Hence, research output and quality should increase with the size of institutions.

While Jordan et al. (1988, 1989) and Meador et al. (1992) conclude that "publishing productivity rises with faculty size at a diminishing rate" (p.347), Golden and Carstensen (1992a,b) dispute the impact of department size on per capita publications (see Abramo et al., 2012, for a summary on that topic and a recent study). Studying a Stackelberg differential game between journal editors and authors, Faria and Goel (2010) propose that a larger network (e.g. being at a larger department) has a positive effect on an author's number of citations but not on her number of publications or research quality.

C.3.2. Data

In order to investigate this question, we resort to IDEAS (`ideas.repec.org`). Based on the RePEc archive, IDEAS is the largest bibliographic database dedicated to economics as it indexes over 2,600,000 items of research and more than 50,000 authors (as of 03 September 2018). Among other things, IDEAS also ranks institutions and authors by a performance score. We will use that score for our analysis.

The IDEAS average rank score is determined by taking a harmonic mean of the institution's rank relative to a corresponding sample (e.g. within a region) in each RePEc criterion. On IDEAS, authors, institutions, journals, and countries are ranked according to (variations of) the number of works registered with RePEc, citation counts, journal page counts, abstract views and downloads, and the author's network (see Zimmermann, 2013, for a description of all criteria). Across criteria, the rank of a specific author or institution might vary. According to Zimmermann (2013) this entails the risk of cherry picking by authors and institutions themselves, editors, and publishers. Therefore, IDEAS uses the harmonic mean of the ranks of all criteria to calculate a score. Aggregating ranks, a lower score is better than a higher one.

C.3.3. Data collection

For the analysis we first use DataGorri's feature to add similar links to the scraper's link list. The website `https://ideas.repec.org/top/top.country.all.html` lists all countries that have research output catalogued in the RePEc archive. Entering this link into the modeler returns the corresponding table including the links to all countries with research institutions or authors in RePEc. Clicking on "Add all similar links to the scraper's linklist" copies all links to the link list. At this step an exceptional issue arises.

The links provided in the table lack "/top/" to form complete links like https://ideas.repec.org/top/top.usa-ma.html. Instead links without target like https://ideas.repec.orgtop.usa-ma.html are provided. The missing part can be inserted between "org" and "top" manually using any word processor. This demonstrates that, despite its convenience, DataGorri still provides enough flexibility to its users.[4] Afterwards, we copy the list of links to DataGorri's link list and save it (we will refer to this list as country link list).

Second, we take the first link to the top 25% institutions and authors in Massachusetts, USA (http://ideas.repec.org/top/top.usa-ma.html, or any other link from the country link list we want to scrape) and enter it in the modeler. DataGorri returns the two tables on the page containing the top 25% institutions (Figure C.3) and the top 25% authors (which we will not use) in Massachusetts. We will scrape the corresponding tables listing each country's top 25% institutions, country by country. Clicking on the first header opens the content of the respective table: rank in the corresponding country, worldwide ranking, institution, score, number of authors, and author shares. We select to scrape all variables by ticking the corresponding boxes and assign meaningful output labels. Finally, we save the generated page model for this table and define it as the institutions page model. This model can now be applied to all items in the country link list.

Now, with the institutions page model and the country link list at hand we return to the "SCRAPER" tab. First, we select the institutions page model in the drop-down menu for page models. Next, from the drop-down menu for link lists, we select the country link list containing the links to all countries in RePEc. Finally, we choose a meaningful name for the result file and click on scrape. On our machine[5], the download took three minutes. The request results in a .csv file containing observations on 2,633 institutions representing the top 25% in their respective country (as of 03 September 2018). The file can now be imported to any common statistics software and analysed.

[4]The option to select a different delimiter than the default (;), and to choose between UTF-8 and Latin-1 character encoding are further features that increase DataGorri's flexibility.

[5]Windows 7, 64 Bit, 3.60 GHz, 32 GB Ram, 100 Mbit/s.

Top 25% institutions in Massachusetts (United States), all authors, all publication years

Rank	W.Rank	Institution	Score	Authors	Author shares
1	[2]	National Bureau of Economic Research (NBER) Cambridge, Massachusetts (USA)	1.4	381	84.15
2	[1]	Department of Economics, Harvard University Cambridge, Massachusetts (USA)	1.6	76	62.56
3	[3]	Economics Department, Massachusetts Institute of Technology (MIT) Cambridge, Massachusetts (USA)	3.13	49	39.28
4	[4]	Kennedy School of Government, Harvard University Cambridge, Massachusetts (USA)	4.45	74	40.19
5	[5]	Department of Economics, Boston University Boston, Massachusetts (USA)	5.33	58	52.74

Figure C.3.: Excerpt of a screenshot of the top 25% institutions in Massachusetts (United States) on https://ideas.repec.org/top/top.usa-ma.html (Accessed 03 September 2018).

C.3.4. Results

To examine the correlation between an institution's performance and its size, we consider the institutions' IDEAS scores and their number of authors on RePEc.

As Figure C.4 shows, the IDEAS score improves with the logarithmic number of authors.[6] This relationship is highly significant (Pearson's Correlation coefficient $= -0.2106$, $p < 0.0000$) and is further substantiated in regressions that control for country effects (Table C.4 and Figure C.4).[7] Since the number of authors is in log scale, an increase in the number of authors per institution of equal size is associated with a larger improvement of the IDEAS score the fewer authors an institution comprises. One can consider this as decreasing returns to scale.

Hence, similar to Jordan et al. (1988, 1989) and Meador et al. (1992), we find a positive correlation between the number of authors per institution and the performance of institutions measured in IDEAS scores. However, this positive relationship is decreasing

[6] Note that the IDEAS rank per criterion and, thus, also the IDEAS score is calculated for each country in our country link list separately. Hence, each country has distinct rankings for all criteria, which are also aggregated on country level only.

[7] As the variable IDEAS Score exhibits overdispersion (its variance is greater than its mean), a negative binomial regression is more appropriate than a poisson regression.

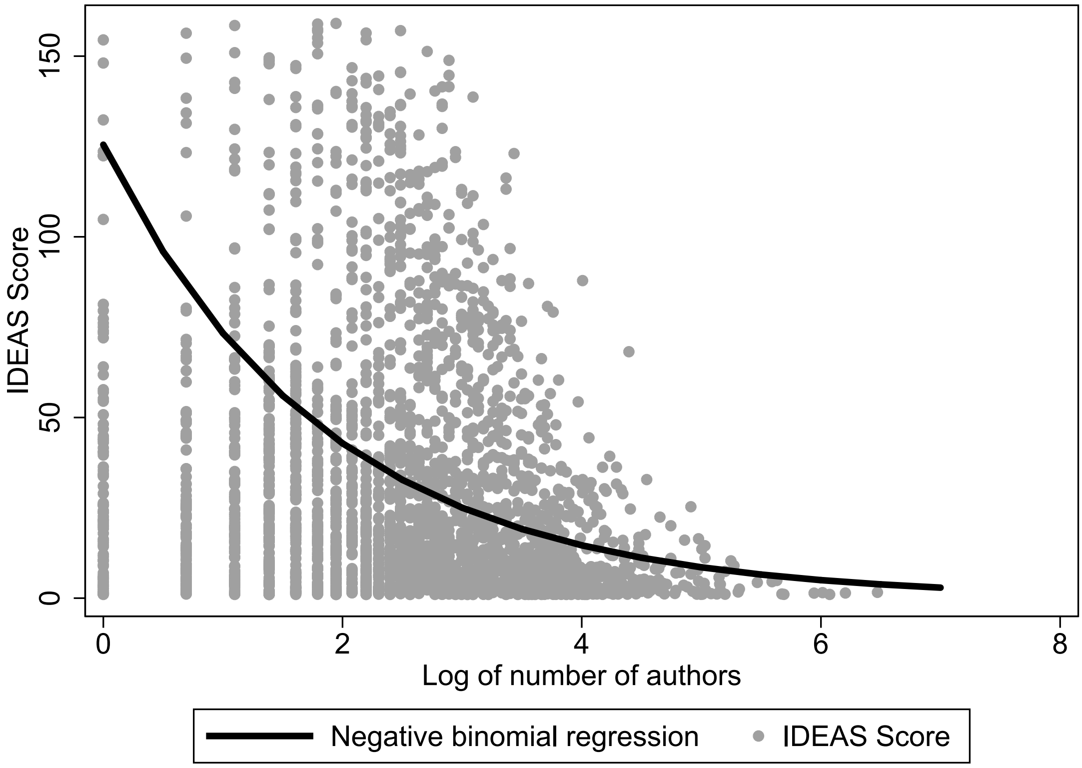


Figure C.4.: Log of number of authors per institution and institution's IDEAS score on ideas.repec.org.

Table C.4.: Poisson and negative binomial regression of the institutions' IDEAS score on their number of authors registered on RePEc.

	IDEAS Score	
	Poisson regression	Negative binomial regression
Log of authors	-0.430***	-0.537***
	(0.00353)	(0.0113)
Constant	0.958	1.055
	(0.545)	(0.620)
Country Effects	Yes	Yes
Log likelihood	-13,870.695	-9,328.452
Pseudo R^2	0.714	0.201
Observations	2,597	2,597

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

with the number of authors per institution. Obviously, the causality could go in both directions. Better institutions could attract more funding and could therefore also hire more scholars. Alternatively, a higher number of academics per institution could result in more interaction between them and could lead to better and more output. Identifying the causal direction thus requires further research. Also, the IDEAS score is an aggregate measure. Therefore, it can not be used to estimate how citations, quality, and number of publications are individually affected by institution size (c.f. Faria and Goel, 2010). Further empirical work is necessary to uncover these relationships.

C.4. Advantages and Limitations

DataGorri's advantages are manifold. While it has already been tested and applied extensively, we are sure that further applications beyond our scope exist. In any case, DataGorri is able to save researchers a substantial amount of time. The more websites a scholar wants to compile data from, the more they benefit from DataGorri. Using the program merely requires a small amount of upfront effort in setting up the page model, but it can be scaled to an unlimited number of websites thereafter. The two options for gathering links described above help reduce the work necessary for the latter.

DataGorri is specialised to scrape tabular data. Hence, it cannot extract data contained in unstructured texts. Other tools exist for such purposes.

In order to provide some degree of automation, the tables in question need to look alike and be located at the same position within a website.

Furthermore, DataGorri does not recognise whether a table is repetitive or not. It therefore requires some user feedback. We aim to tackle some of these issues in future releases of the program.

C.5. Conclusion

In this paper, we introduced DataGorri, a software that enables researchers to collect repetitive and non-repetitive tabular data that is available on websites. For that purpose, DataGorri runs through a list of predefined links, which all contain the same type of table, and exports the tabular data to a .csv file format.

We are aware of the fact that compiling online data can be a cumbersome task and very time-consuming. We provide DataGorri free of charge. However, we require to be cited whenever DataGorri has been used for scientific research (cite ware). This ensures that more colleagues will learn about DataGorri and are able to benefit from using it. Sometimes scientific work is impeded by preparatory efforts. With DataGorri, we hope to lower this hurdle.

Appendix D.

Appendix to Section II.2

D.1. Instructions

Dear participant,

to begin with, I would like to thank you for partaking in this experiment.

For this experiment, we do not use Euro as our currency, but **ECU (Experimental Currency Units)** instead. Upon completion of the experiment, the **ECUs** you have earned will be converted to **Euro**. The exchange rate equals **10 ECU = 0.60 EURO**. After the experiment ends, randomly selected students will receive the payoff they have obtained.

This experiment consists of two parts: the first requires you to fulfil a task, in the second you will be asked to invest ECUs.

Part 1: Task

To complete part one of the experiment, 10 rows of circles must be filled in while either 1, 5 or 9 rows have already been filled in. For completing this task you receive an initial endowment of **100 ECU**. To participate in the draw, determining which students receive monetary payoffs, all rows must be filled in.

Part 2: Investment

In part two you anonymously play an economic game with two other participants. The amount of rows these participants had to fill in was randomly determined.

This game provides you with the option to invest a share of your initial endowment. The investment of all three group members is added up, then **multiplied by 1.5** and subsequently **split evenly among all three group members**.

The share of your initial endowment you chose not to invest, goes directly towards your balance at the end of a round.

$$\text{Payoff} = (\text{Initial Endowment} - \text{Investment}) + 1/3 \cdot (1.5 \cdot \text{Sum of Investments})$$

Example:

Of her 100 ECU initial endowment, a participant (group member 1) decides to keep 20 ECU and invest 80 ECU. The two other group members decide to invest 40 ECU (group member 2) and 60 ECU (group member 3), respectively. In total, 80 ECU + 40 ECU + 60 ECU = 180 ECU were invested. Multiplied by 1.5, this amounts to 270 ECU, which is then divided evenly among all group members (90 ECU per person). As a result, the individual group members receive the following payoffs:

- Group member 1 keeps the 20 ECU she did not invest and receives an additional 90 ECU from the investment, a total of 110 ECU.

- Group member 2: 60 ECU (= 100 ECU - 40 ECU) + 90 ECU (Investment) = 150 ECU.

- Group member 3: 40 ECU (= 100 ECU - 60 ECU) + 90 ECU (Investment) = 130 ECU.

Payoff

Following this experiment, all task and decision sheets will be collected. For this reason, please detach this sheet from the second one. After the collection of the sheets, the winners will immediately and anonymously be determined. These individuals' responses will be used to calculate their respective payoffs. In the case of an incomplete response sheet, the draw will be repeated. The winners will be able to receive their payoffs at my office (2423) after presenting their title sheet and subject id/participant number, which can be found at the end of all sheets.

Task Sheet (separate page)

Please fill in all empty circles with a ballpoint pen.

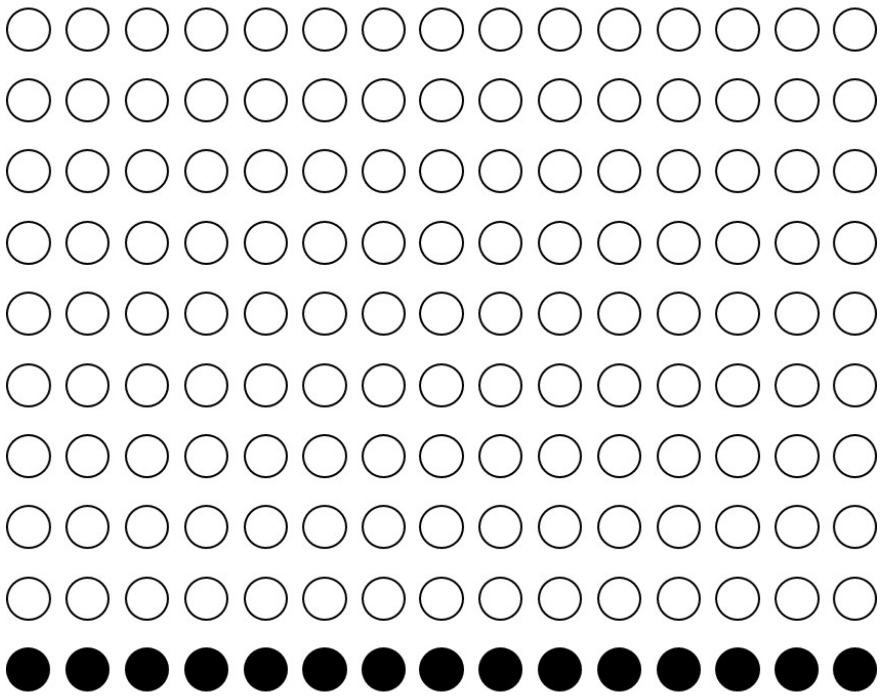


Figure D.1.: Circles to be filled in by participants.

Decision Sheet (separate sheet)

Investment Decision

What amount would you like to invest?

Please choose a number between 0 and 100. Note that any amount of this endowment, which you choose not to invest is counted directly towards your payoff.

Additional Questions

1.	A bat and a ball together cost 110 cents. The bat costs 100 cents more than the ball. How much does the ball cost? (in Euro)	Euro
2.	If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? (in minutes)	Min
3.	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? (in days)	Days

Risk preferences

Assess yourself: Are you more of a risk-taking person or do you think of yourself as a risk-avoider? Please tick a box on the scale below, 0 indicating “no tolerance for risk” and 10 indicating “very risk-seeking”. The values in between can help you more finely represent your image of yourself.

☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7	8	9	10

Demographic Information

In closing, I would like to ask you to give some information on yourself. It is important for analysing the data created in this experiment and will be treated strictly confidentially.

Your gender: ☐ Female

☐ Male

Your age: ☐

Your final math grade: ☐

D.2. Robustness Checks

Table D.1.: OLS regression results for *Contribution* using binary (*High CRT*, (1)) and continuous (*Correct*, (2) and (3)) measurements of cognitive ability, and binary (*High Effort*, (1) and (2)) and continuous (Effort Level, (3)) treatment variables.

	(1)	(2)	(3)
High Effort	-22.155**	-35.144**	
	(8.171)	(11.446)	
Effort Level			-0.438**
			(0.143)
High CRT	-15.839*		
	(7.407)		
Correct		-8.090*	-8.649*
		(3.678)	(3.951)
High Effort × High CRT	29.033*		
	(12.559)		
High Effort × Correct		12.271*	
		(5.365)	
Effort Level × Correct			0.144*
			(0.066)
Age	0.349	0.213	0.519
	(1.282)	(1.356)	(1.054)
Male	-0.112	1.516	0.274
	(5.910)	(5.956)	(4.758)
Constant	60.299*	71.385*	65.988**
	(27.453)	(30.305)	(23.905)
Session Effects	Yes	Yes	Yes
N	116	116	154

Notes: The variable *High Effort* is a binary variable, which takes a value of one if the subject is assigned to the *High Effort* treatment and zero for the *Low Effort* treatment. Therefore, the regression is run on 116 observations of the *Low* and *High Effort* treatment in Specifications (1) and (2), excluding those of the *Medium Effort* treatment. Specification (3) includes the 38 observations from the *Medium Effort* treatment. The variable *Effort Level* is the relative amount in percentages of circles that the participant had to fill in. *High CRT* is equal to 1 if the subject has answered all CRT questions correctly and 0 otherwise. The variable *Correct* is the number of correctly answered questions in the CRT. Male is equal to 1 for males and 0 otherwise.

Heteroskedasticity robust standard errors in parenthesis.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

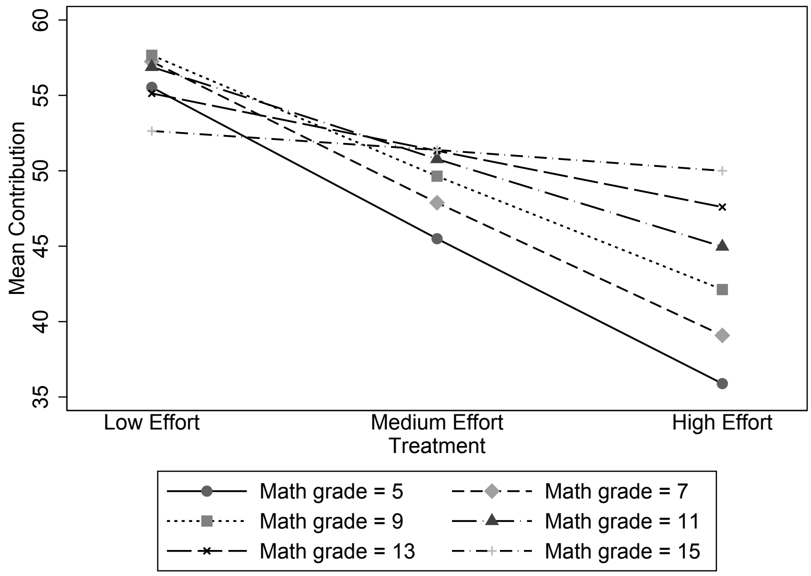
Table D.2.: Maximum likelihood estimates of the Hurdle model of contributions using the continuous treatment variable (*Effort Level*) and the final math grade of the students as a measure for cognitive ability.

	Contribution	Selection (Probit)
Effort Level	-0.561*	0.004
	(0.264)	(0.016)
Final math grade	-2.513	0.138
	(1.324)	(0.095)
Effort Level × Final math grade	0.036	-0.000
	(0.023)	(0.001)
Age	1.398	0.009
	(1.107)	(0.083)
Male	8.148	-1.209*
	(4.942)	(0.539)
Constant	57.160*	0.689
	(27.585)	(1.959)
Session Effects	Yes	Yes
N	147	

Notes: The variable *Effort Level* is the relative amount in percentages of circles that the participant had to fill in. The final math grade ranges from 0 (worst grade, no observations) to 15 (best grade). A minimum of five points is required to pass. The variable has a mean of 10.97 and is only available for students with grades conforming with the German system (N = 147). Male is equal to one for males and zero otherwise.

Heteroskedasticity robust standard errors in parenthesis.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



Notes: The final math grade ranges from 0 (worst grade, no observations) to 15 (best grade). A minimum of five points is required to pass. The variable has a mean of 10.97 and is only available for students with grades conforming with the German system.

Figure D.2.: Mean contributions by treatment group and math grade as estimated by the Hurdle model in Table D.2.

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