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Mining for mood effect in the field[*]

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Abstract

We conduct what we believe to be the most methodologically rigorous study of mood effect in the field so far to measure its economic impact and address shortcomings in the existing literature. Using a large dataset containing over 46 million car inspections in Sweden and England in 2016 and 2017, we study whether inspectors are more lenient on days when their mood is predicted to be good, and if car owners exploit the mood effect by selecting these days to inspect low quality cars. Different sources of good mood are studied: Fridays, sunny days, and days following unexpected wins by the local soccer team, with varying degrees of the car owner's ability to plan for inspection, and hence the likelihood of selection bias. We find limited evidence to support the existence of mood effects in this domain, despite survey results showing belief to the contrary. There is some indication of selection effect on the part of car owners. Our findings cast doubt on previous mood effects found in the field.

Keywords: mood effect; selection bias; car inspection

JEL codes: D12; D22; D84; D91

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1. Introduction

Economists are increasingly acknowledging the role played by emotions and mood in decision-making (Card & Dahl, 2011; Hirshleifer & Shumway, 2003; Loewenstein, 2000).[1] Laboratory experiments that randomly manipulate the mood of subjects find that mood does affect behavior (Capra, 2004; Harding & He, 2016; Hertel et al., 2000; Johnson & Tversky, 1983; Kirchsteiger et al., 2006; Kuhnen & Knutson, 2011; Wright & Bower, 1992). However, less is known about how much mood matters in real life, that is, outside the highly controlled laboratory setting. How large is the economic impact of mood effects, and is this something that is exploited, and possibly neutralized, by sophisticated economic actors? Answering these questions requires a careful study of mood effects in a field setting. Our paper does this using car inspections, a unique setting where there exists a belief that extraneous factors such as weather and weekday affect inspection results through inspectors' mood.

Our paper provides several key contributions. First is our systematic analysis of mood effects using multiple mood sources: Fridays, good weather and unexpected sports wins. To highlight its importance, consider the typical study of mood effect in the field: given that mood is unobservable, the author(s) picks a *single* mood trigger, such as the weather, takes as given that it impacts mood, and analyzes its effect on behavior, for example on the stock market (Goetzmann et al., 2015; Hirshleifer & Shumway, 2003). If an effect is found, it is attributed to the weather's impact on investors' mood. This methodology implies an instrumental-variable approach: the weather is used as an instrument since it should not affect the stock market unless through mood. However, the "first stage" relationship has never been established as mood is not directly measured. We argue therefore that mood is not cleanly identified in the existing studies; it is unclear if any effect on behavior is truly attributable to mood rather than other factors related to the source itself. In addition to spurious correlation, using a single mood source increases the risk of false positives and, given publication bias, the related pitfall of data-mining. By using multiple mood sources in our analysis, we pose extra tests on the data generating process that should confirm the existence of mood effect, if such an effect is genuinely identified. Our analysis shows that the different mood sources give remarkably different interpretations of the same outcome variable. That we do not find consistent effects leads us to conclude that the role played by mood in field settings in previous highly cited studies, such as the financial market, may be overstated.

Second, ours is the first paper that studies mood effects from both sides of the market: inspectors and car owners. Previous studies of mood effects using financial market data are typically based on measures aggregating multiple sides of the market such as stock returns (Edmans et al., 2007; Hirshleifer & Shumway, 2003; Saunders Jr, 1993), buy minus sell volumes (Goetzmann et al., 2015) or percentage of buy transactions (Kaustia & Rantapuska, 2016). This means that we cannot separate the effect of weather-induced optimism on one side from the strategic behavior of the higher-level thinkers on the other side who refrain from selling to keep prices high.[2] We are able to address this problem in our analysis of inspectors'

[1] While psychologists often write about mood and emotion as two different affective states, economists seldom rely on this distinction. We therefore use the term "mood" throughout. Further conceptual discussions are provided in Section 2.

[2] Experimental evidence suggests that a substantial proportion of subjects are higher-level thinkers of at least order 1 (Camerer et al., 2004; Nagel, 1995).

behavior given our rich set of control variables on car characteristics. An additional way in which we control for this “selection effect” is by using multiple mood sources with varying degrees of predictability, which allow us to compare the extent to which car owners are able to strategically select inspection days. Our dataset also enables us to study car owners’ likelihood of choosing days when inspectors are anticipated to be in a good mood. Our finding that lower quality cars do select into good mood days highlights the importance of taking into account such higher-level thinking when studying mood effects.

Our third contribution is our car inspection setting, which possesses many suitable characteristics for analyzing the effect of mood on decision-making. Deciding the outcome of a car inspection involves clear elements of cognitive processes where mood, according to psychological theories, plays a role. There is also a potentially important social factor since the car owner is directly and financially affected by the inspection outcome and previous research suggests that mood affects pro-sociality (Kirchsteiger et al., 2006; Rind, 1996). Previous studies of the car inspection markets have also shown that inspectors exercise a certain degree of discretion and respond to what should be irrelevant factors, such as the perceived wealth of the customer and the degree of competition around the inspector’s station (Gino & Pierce, 2010; Habte & Holm, 2017; Hubbard, 2002). Unlike stock market behaviors which are sensitive to shocks from e.g. macro news, car inspection outcomes should be relatively stable over time and hence it is a setting in which mood effects, if any, can be more cleanly detected. Finally, car inspection is also a domain in which there is a common belief that mood may affect outcomes. For instance, a common anecdote in Sweden is that smart car owners inspect their cars on Fridays because on these days the inspectors are in a good mood and will be less likely to fail their car. We confirm this belief using a survey of 517 Swedish car owners, where we find there does exist a belief that car owners take weekday and weather into account to increase the chance of passing an inspection.

Our fourth and final contribution is our large dataset containing 46 million car inspections in Sweden and England during 2016 and 2017. The large number of observations makes this study highly powered to detect small effects, which is potentially another concern with the existing studies using much fewer observations. The obtained micro dataset includes a large number of control variables allowing us to indirectly study if the car owners strategically exploit mood effects, and hence isolate mood’s effect on inspectors. The data from two different countries also allows us to study whether institutional differences matter for mood effects. In Sweden, car owners have five months to select when they want to go for inspection, while in England they only have one. This may potentially allow a stronger selection effect to persist in Sweden.

We systematically investigate the potential effects of several sources of good mood on inspection results: Friday, good weather, and unexpected sports wins. If indeed these variables significantly affect inspectors’ mood, we should expect to find “mood effect” revealed as consistently lower failure rates on Fridays, sunny days, and following sports wins. Our rich dataset allows us to detect and control for selection effects, whereby low quality cars are more frequently inspected on days predicted to generate good mood in inspectors. Additionally, by using different mood sources with varying predictability we are also able to address this issue. Our preferred specification regresses inspection outcome on the good mood indicator and controls for other car characteristics including mileage, inspection year, green fuel, car make, and geographical area fixed-effects. We also separately study the extent to which car owners behave strategically to exploit any mood effect on inspectors, hypothesizing that car quality as proxied by mileage is lower (higher mileage) on good mood days. Any selection effect is expected to be stronger on Fridays, which can be easily planned for, and less on sunny days and following unexpected sports wins, which cannot be predicted perfectly. Our preferred specification regresses the good mood indicator on mileage and the above controls.

Our main result is that mood does not have a consistent effect. The only situation in which mood has an effect in the predicted direction is on Fridays in England, when failure rates are around 5.11% lower. In other cases, we find the opposite effect: failure rates are *higher* on sunny days in England (1.01%), and on Fridays in Sweden (4.86%). No significant effect is found on sunny days in Sweden or following unexpected sports wins in either country. Similarly inconsistent findings are obtained when analyzing bad mood days. These results underline the importance of using multiple mood sources to avoid drawing hasty conclusions regarding the impact of mood on decision-making and cast doubt on previous studies that rely only on a single mood source. For example, we find no mood effect using the data from Hirshleifer & Shumway (2003) when mood is proxied using Friday or, using the method of Edmans et al. (2007), wins by the national soccer team. Overall, our results show that mood has no clear effect in this domain, even if there is widespread belief about it.

We find some indication of strategic behavior on the part of car owners: the average car quality is indeed lower on Fridays, but the effect is small. As expected, the selection effect is slightly smaller in England where owners have a smaller window for selection. Our analysis of bad mood days confirms car owners' strategic avoidance of Mondays when inspectors are anticipated to be in a bad mood. Less consistent selection bias is observed for good mood days which are more difficult to target, including sunny days and after unexpected sports wins.

The remainder of the paper is structured as follows. In Section 2 we discuss the concept of mood and summarize the literature on the theory and evidence of mood effect on behavior. We elaborate on the issues we identify in the existing literature and how our study addresses the resulting gap. We provide information about the car inspection setting in Sweden and England in Section 3. Section 4 details the survey conducted on Swedish car owners, establishing the existence of belief about mood effects. We describe our datasets in Section 5. Our results are provided in Section 6, starting with a brief summary followed by analyses of mood effects in declining order of predictability. In Section 7 we illustrate that a systematic analysis of mood effect using the data from Hirshleifer & Shumway (2003) yields a different conclusion when multiple sources are used. We conclude in Section 8.

2. Theory and evidence about mood effects

The notion of mood is potentially very important in economics since it may fundamentally change how decision-making is analyzed. Despite this, the literature is characterized by scattered empirical efforts. It is not always clear what researchers mean by a given mood effect and their conceptualization is not always consistent. Furthermore, there is no clear agreement as to how mood effects should be viewed from a theoretical economic perspective.[3] These are important questions that need to be addressed by a serious research agenda studying mood effects.

In this section, we, therefore, begin by defining the concept of mood, mood effect, and how it changes the theoretical analysis of decision-making. We continue with a discussion of the theoretical mechanisms that can explain how mood affects behavior and report the laboratory experimental evidence. Next, we discuss the effects of sunlight, weekdays and sports results on mood. Given that mood is not observable in the field, these external factors have commonly been used as mood proxies. In the last subsection, we discuss the existing studies, the problems we see with this approach, and how these are addressed by our current study.

2.1 Mood, mood effect and the theoretical analysis of decision-making

The APA Dictionary of Psychology defines mood as “any short-lived emotional state, usually of low intensity (e.g., a cheerful mood, an irritable mood).” (VandenBos, 2007). This is the working definition we use in this paper and we do not qualitatively distinguish it from “emotion”, which is a related concept in psychology. When we talk about mood effects we generally refer to the mood-congruency effect, which is the match in valence between a person’s mood and thoughts, and hence judgments (Mayer et al., 1992). In our car inspection setting, “mood effect” will occur when external factors significantly affect inspectors’ mood such that inspection outcomes are influenced in a congruent direction: higher pass rates on days predicted to generate good mood and vice versa.

From an economic (and philosophical) perspective, it is important to stress that “mood” refers to some form of internal emotional state and that this state (in addition to other factors like information and preferences) may be unobservable and matters for behavior. As described by Isen (1984), mood states “gently color and redirect ongoing thoughts and actions, influencing what will happen next but almost without notice and certainly without ostensibly changing the context or basic activity.” Mood thus complicates the analysis of behavior since the same observable external factor may result in different reactive behavior depending on what internal mood state the actor is in.[4]

2.2 Effects of mood on behavior

There are two major theories that seek to explain the qualitative, informational role of affect in decision-making, specifically the significant mood-congruent biases found in many studies (Mayer et al., 1992; Westermann et al., 1996). The first is the mood-priming model, in which mood acts as a cue that primes the subject to more easily focus on mood-congruent material, which on the other hand makes focusing on mood-incongruent material cognitively taxing (Bower, 1981; Carlson et al., 1988; Forgas & Bower, 1987, 1988; Isen et al., 1978; Isen, 1984). Hence, subjects in a good mood will find positive material more salient and vice versa. The second theory is termed mood-as-information. In this process, subjects misattribute their

[3] Loewenstein (2000) models the effects of visceral factors using state-dependent preferences, but, as he concedes, there are complications associated with this approach. For example, visceral factors can drive people to behave contrary to self-interest and their impact on behaviour is often underestimated,

[4] In the appendix we present an illustration of how mood affects the behavior of a car inspector as a simple Moore machine.

affective states for information and use mood as a shortcut to infer their evaluative reactions to the (unrelated) target (Clore et al., 1994; Schwarz, 1990; Schwarz & Clore, 1983, 1988; Slovic et al., 2007). Hence, subjects in a good mood will assume that their mood is due to the material being evaluated, which must, therefore, be positive.

Regardless of the mechanism, studies have found that subjects who are in a good mood tend to be more optimistic, attaching greater probability to positive events and more tolerant of risk (Bassi et al., 2013; Johnson & Tversky, 1983; Kuhnen & Knutson, 2011; Wright & Bower, 1992), translating to more positive returns on the stock markets (Goetzmann et al., 2015; Hirshleifer & Shumway, 2003). They have a more positive evaluation of other people (Forgas & Bower, 1987), consumer goods and brands (Batra & Stayman, 1990; Isen et al., 1978), and life satisfaction (Schwarz & Clore, 1983). If mood effect is present in our setting, an inspector who is in a good mood when conducting a car inspection is more likely to tolerate defects in borderline cases and have a positive evaluation of the car being inspected, and consequently pass more cars.

The effect of mood on behavior is not limited to what, but also how decisions are made. Several studies have reported that people in a good mood tend to use more simplistic and heuristic information processing while bad mood tends to stimulate more careful and analytical information processing (Batra & Stayman, 1990; Bless et al., 1990, 1996; Hertel et al., 2000; Park & Banaji, 2000; Schwarz & Clore, 1983; Sinclair & Mark, 1995). This is argued to be a form of mood maintenance strategy, whereby people in a good mood avoid investing cognitive effort unless it will maintain or enhance their positive mood (Isen et al., 1988; Isen & Simmonds, 1978; Wegener et al., 1995). In our car inspection setting, inspectors' good mood is thus expected to make them more receptive to positive information and overlook issues with the car. Bad mood is expected to make inspectors more inquisitive and take a second look at potential safety issues. These effects go in the same direction as those predicted in the previous paragraphs. Hence, failure rate is expected to decrease on days when inspectors are expected to be in a good mood and vice versa.

2.3 Effects of external factors on mood

Below we will present evidence relating to three external factors that have been claimed to affect mood, namely sunlight, the day of the week, and sports results.

Sunlight: There is strong clinical evidence for the positive effect of sunlight on mood. Sunlight increases vitamin D and serotonin production (Lansdowne & Provost, 1998). A lack of sunlight in the fall and winter months can give rise to a clinical syndrome known as seasonal affective disorder (SAD), and exposure to bright light is found to immediately improve mood (Kripke, 1998; Rosenthal et al., 1984). Additionally, sunshine can improve mood through symbolic associations with positive events (Cunningham, 1979). As a result, people report themselves to be happier and have higher life satisfaction on sunnier days (Schwarz & Clore, 1983).

Weekdays: The cyclical effect of weekdays on mood has been widely studied in the psychological literature, focusing on the commonly held belief of the "Blue Monday", "Thank God it's Friday" and weekend effects. People associate Mondays with more negative mood which improves as the week progresses and the weekend approaches (Larsen & Kasimatis, 1990; Reis et al., 2000; Stone et al., 2012). This can be explained by, for example, the fact that people experience more autonomy and closer relations to others on weekends and not during workdays (Helliwell & Wang, 2014, 2015; Reis et al., 2000; Ryan et al., 2010). Consequently, the anticipation of the upcoming weekend generates pleasure that is already experienced on Fridays, while the end of the weekend and the anticipation of the upcoming workweek lead people to associate Mondays with negative emotions. However, studies based on actual momentary mood, as opposed to recalled or predicted mood, have not found complete support for this effect, showing little or no variation by day (Areni & Burger, 2008; Stone et al., 1985; Totterdell & Reynolds, 1997). This discrepancy has been attributed to the widespread systematic bias in remembered utility when people are asked to recall past feelings (Kahneman, 1999), or a form of projection bias where people exaggerate the degree to which their preference for Friday will resemble their current taste (Loewenstein et al., 2003). Overall, while there is little to suggest that actual mood displays an improvement over the week from a minimum on Monday, there is more robust evidence that people, in any case, *expect* this variation in mood. Hence, car owners may expect that inspectors are more lenient on Fridays even if inspectors are not actually in a better mood on Fridays.

Sports results: The only study we are aware of that looks at the effect of sports results on (self-reported) mood is Schwarz et al. (1987). During the 1982 soccer world championship, male respondents in a German city were contacted before or after one of two games in the first half of the championship, one resulting in a win and the other a draw. The results appear to support the mood-as-information theory. The self-reported variable of global well-being is higher after a win, but lower when the game is tied. No significant results are obtained for specific domains such as satisfaction with work and income, in which respondents are predicted to have a lot of information and well-defined criteria for evaluation, and hence less need to seek for clues in their mood.

2.4 Mood effect in the field: effects of external factors, as proxies for mood, on behavior

Studies of mood's effect on behavior are typically conducted in a laboratory setting, where mood is manipulated and the effects on behavior are elicited a short time after. In a field setting, mood cannot be manipulated in a similarly controlled manner. Researchers have thus turned to external factors such as weather, weekday or sports results, which have been speculated to affect mood, to study if the good mood induced by these events has any substantial effect on behavior. Two well-known studies have found that clear sky increases returns on the stock market (Hirshleifer & Shumway, 2003; Saunders Jr, 1993), attributing the effect to the increased optimism of investors whose mood improves with sunny weather. However, Loughran & Schultz (2004) do not find that cloudiness affects returns for local stocks, despite evidence that much of the trade was conducted by local investors. Neither is there robust effect of cloud cover on trading activities. Increased cloud cover is found to decrease analysts' activities (Dehaan et al., 2017) and is associated with perceived overpricing, thus indicating pessimism on the stock market (Goetzmann et al., 2015). Goetzmann et al. (2015) find reduced trading activity for institutional investors on cloudy days, while no significant effect is found for retail investors (Goetzmann & Zhu, 2005). Kaustia & Rantapuska (2016) find no effect of cloudiness on buy activity when including all market participants. The effect of sunniness on other types of behavior has also been studied in Riener & Traxler (2012), finding higher voluntary payments for restaurant meal on a sunny day during the autumn, while more sunshine decreases payment in the summer. de Silva et al. (2012) also find that weather-induced mood affects art auction prices, though the effect is limited to the lower end of the price distribution.

While cloud cover is the most commonly used mood proxy, there also exist a number of studies that use rainfall as an indicator of mood, with mixed findings. Meier et al. (2019) show that rain on an election weekend causes higher risk aversion, thus decreasing votes for political change. Goetzmann & Zhu (2005) also investigate the effect of rain on stock returns, however, no significant effect is found. Kaustia & Rantapuska (2016) find the opposite: precipitation has a strong statistical and economic effect, while sunniness does not.

Kaustia & Rantapuska (2016) also study the effect of weekday. Their motivation for including Friday, however, is to check for calendar effects rather than mood effect caused by looking forward to the weekend, and this is done by controlling for Friday in the weather regression model.[5] Friday is found to have positive effects on trading activity and this is explained by investors' desire for mental closure. Saunders Jr (1993) also mentions that returns in the New York stock exchange is correlated with Fridays, but no estimates are given (p. 1342). Goetzmann et al. (2015) check for any Monday effect, finding a negative effect smaller than that from cloud cover on investor's Buy-Sell Imbalance.

Finally, several papers have looked at the effects of sports results on behavior. Card & Dahl (2011) find that upset losses lead to an increase in domestic violence, while upset wins do not have any significant effect. Similarly, Edmans et al. (2007) find a significant decrease in stock index returns following international soccer losses but no effect after wins. Chang et al. (2012) use the relation between NFL results and the returns for Nasdaq firms headquartered near the NFL team, also finding that loss leads to lower next-day returns and that the impact increases when the loss is surprising or critical. On the other hand, Lindo et al. (2018) only find that upset wins are associated with significant increases in reports of sexual assaults, while Kaplanski & Levy (2010) find that any effect of sports match on stock returns is independent of the game's result. Healy et al. (2010) also find that wins by the local college football team have an effect on US government elections, causing the incumbent to receive an extra 1.6 percentage points of the vote in the Senate, gubernatorial and presidential elections.[6]

What the above shows is that the literature is characterized by a large number of studies finding that one particular factor, which is hypothesized to affect mood, causes some change in behavior, typically in the stock market. However, the existing literature in our view is insufficient to draw any strong conclusion about mood effect in the field. Two issues that need to be addressed are the use of a single mood source and outcome variables that aggregate multiple sides of the market.

The first problem is that the majority of the existing field studies only use one mood source. Given the diffuse and low-intensity properties of mood, it is difficult to draw the conclusion that mood affects behavior merely from observing that a particular proxy for mood has any effect. For example, Kaustia & Rantapuska (2016) find that buy ratio of stocks is higher

[5] Our conclusion does not change when we control for all mood effects in the same regression. The results are shown in the appendix.

[6] Fowler & Pablo Montagnes (2015) have reassessed the evidence and argue that the finding in Healy et al. (2010) is a false positive. Given replication is not possible for observational work in the social sciences, they recommend that researchers conduct theory-informed tests of hypotheses that should hold if the estimated effect is genuine, an approach we adopt in this paper.

on Fridays compared to other days, but the authors acknowledge that this could be due to investors' desire for mental closure at the end of the week. Suspicions of data mining or spurious correlation have also been raised for the weather effect on stock returns (Kim, 2017; Loughran & Schultz, 2004). If mood truly has an economically and statistically significant effect on behavior, this effect should be observed when other sources of good mood are used. Our study is motivated by this concern and we consequently use three often cited sources of good mood: Friday, good weather and sports results, to check if all of these factors have a consistent effect on inspectors' decisions. To illustrate the importance of considering multiple mood sources, we employ this research method on the dataset from Hirshleifer & Shumway (2003). As will be shown in Section 7, while the weather effect on stock returns is robust, Friday or sports win has no effect, indicating that the role played by mood in this setting is far from clear.

The second problem is the use of an outcome variable that is not able to separate between the behaviors of various actors. If mood is anticipated to affect one actor in a market interaction, this can be exploited by a rational agent on the other side of the interaction. This is a problem when using stock market trading activity to study mood effect. When stock returns or buy-sell imbalances are observed to be higher on a sunny day, it is unclear if this is driven by optimistic buyers who are in a good mood and buy more or other rational traders who anticipate the buyers' good mood and wait longer before selling their stocks. Using other decision-making domains can potentially remedy this problem, given good controls. In our setting, owners of low quality cars have an incentive to select inspection days when the chance of passing is highest.[7] Assuming first-order beliefs, if owners of low quality cars seek to take advantage of inspectors' good mood, they would rationally target good mood days for inspection. However, since our data contains many variables for car characteristics including indicators of quality, we are able to control for this selection effect and more cleanly identify mood effect. Furthermore, using multiple mood sources also enables us to more cleanly study the behavior of inspectors on days when good mood cannot be predicted in advance by sophisticated car owners.

3. Car inspection rules in Sweden and England

Swedish law requires that each car undergo regular inspections at an approved company to test its roadworthiness, concerning safety and environmental impact.[8] Prior to 20 May 2018, when fixed inspection periods were eliminated, the car owner could inspect the car during a five-month period based on the last digit of the car's registration number.[9] Failing the inspection means that the car has to come back for re-inspection, typically within 30 days, but if the car has failed three times in a row the re-inspection needs to be done within 7 days. There are a total of 599 inspection stations in our dataset. The law forbids an inspection station from also conducting repairs.[10] A typical inspection costs between 430-479 SEK depending on the

[7] In the appendix we provide a theoretical model that explains why low quality cars are more prevalent on days when inspectors' mood is predicted to be good.
[8] The first inspection is to be done within 3 years, then within 2 years, and subsequently every year after: i.e., a 3-2-1-1 rule. For more information, see https://www.transportstyrelsen.se/en/road/Vehicles/motor-vehicle-inspection2/motor-vehicle-inspection-of-passenger-cars-and-lorries-not-exceeding-3500-kg-in-total-weight/, accessed 2019-06-13.
[9] The exact inspection periods are provided in Table 13 in the appendix.
[10] https://www.riksdagen.se/sv/dokument-lagar/dokument/svensk-forfattningssamling/fordonslag-2002574_sfs-2002-574 4 kap 2h§, accessed 2019-05-16.

company though a lower price can be found for choosing unpopular inspection times or locations.[11]

Cars in England are similarly required to undergo a Ministry of Transport (MOT) test regularly.[12] The car owner can choose to inspect the car up to a month (minus a day) before the last test certificate runs out and keep the same renewal date. If they choose to inspect the car earlier, the renewal date for the following year will change to one year (minus a day) from the date the car last passed its test. This means that, practically, there is a smaller window for the car owner to select a preferred inspection day as compared to Sweden. Inspection fees vary, but cannot exceed a maximum of 54.85 GBP.[13] Unlike in Sweden, any individual can apply to run a MOT station, including car repair garages. This results in a higher number of inspection stations, each conducting fewer inspections, as compared to Sweden. There are currently 19,738 inspection stations in England, each of which conducts 1,052 inspections per year. The corresponding number for Sweden is 4,858 inspections.

Despite a clear testing procedure, inspectors still have many opportunities to exercise discretion when applying certain standards. For borderline cases, it can be debatable whether or not the tyre tread is at least 3 mm deep, whether the brake is close to being worn out, and whether there is rust on the chassis of the car, for example. Other studies have also described ways in which inspectors can help certain cars pass vehicle emissions tests, for example by warming the vehicle up before emission readings or substituting other cars during testing procedures (Gino & Pierce, 2010; Hubbard, 2002).

4. Beliefs about mood effect in the Swedish car inspection market

To verify beliefs about mood effect in our setting, we run a survey using a web panel of Swedish adults, 18 years or older, who own a private car. In this section we describe our findings from the survey. The survey questions are provided in the appendix.

In total we collected 517 responses. The average age of our respondents is 51 years old (sd 16.4), 51% are male and 74% are married or live in a domestic partnership. 50% have post-secondary education. Since alternatives are presented in categorical formats, we describe the following characteristics in median instead of mean. The median respondent's total monthly income is between 25,000 – 30,000 SEK and he owns a car from 2011 with 50,000 – 100,000 km in mileage. He has been to 7-9 inspections, passing every time.

The commonly held belief that mood is best on a Friday or a sunny day is supported in our survey data. When asked on which weekday they think most people in Sweden are happiest, 84% of respondents choose Friday, and when asked in which type of weather, 75% choose "clear".

When asked whether they believe that factors such as weekday or weather play a role in whether a car passes inspection, the majority do not think so.[14] However, a non-negligible

[11] https://www.privataaffarer.se/articles/2017/02/10/stora-skillnader-pa-besiktningspriser/, accessed 2019-05-16.
[12] The frequency of inspection follows a 3-1-1 rule. For more information, see https://www.gov.uk/getting-an-mot, accessed 2019-05-16.
[13] https://www.gov.uk/getting-an-mot/mot-test-fees, accessed 2019-05-28.
[14] We were originally also interested in the effect of payday, as a mood proxy, on failure rate. While payday always occurs on the 25th of the month in Sweden (or the closest workday), we have no available data for England. In any case, no payday effect is found in Sweden. The results are available from the authors upon request.

percentage believe that weekday or weather plays a role (15% and 13% respectively).[15] Of those who believe that weekday plays a role, 76% state Friday to be the day on which the likelihood of passing is highest. Of those who believe that weather plays a role, 69% believe that the chance of passing is highest on a clear day. In particular, those who do believe that weekday or weather plays a role are systematically different from those who do not believe these factors matter. As shown in Table 1, those who believe weekday or weather plays a role tend to have older cars with higher mileage and have failed inspections more times than those who do not believe that weekday or weather matters.

Table 1 Belief that weekday or weather plays a role in inspection result

	Weekday		Weather	
	No role	Plays a role	No role	Plays a role
Km	2.79	3.16 (*)	2.79	3.29 (**)
Year	2010	2008 (**)	2010	2008 (**)
No. of inspections	3.60	3.58	3.56	3.85
No. of failures	0.67	1.01 (***)	0.67	1.14 (***)
Obs	437	80	452	65
%	84.53%	15.47%	87.43%	12.57%

Average score by belief of role played by weekday or weather on a car passing inspection. *Km*: mileage where 1 is 0-50,000 km, 2 is 50,000-100,000 km, 3 is 100,000-150,000 km and so on up to 9 which is 400,000 km or higher. *Year*: model year. *No. of inspections*: number of times respondent has inspected their car where 1 is never, 2 is 1-3 times, 3 is 4-6 times, 4 is 7-9 times and 5 is 10 times or more. *No. of failures*: how many times respondent has failed a car inspection with requirement for re-inspection where 0 is never, 1 is once, 2 is twice or more. Result of two-sided t-test of difference between those that believe weekday or weather plays a role and those who do not in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Our takeaway from the survey results is that there is a general belief that mood is best on Friday or a sunny day. However, it is mainly those with low quality cars with more experience of failing an inspection who admit to believing that factors such as weekday or weather matter for inspection results. A possible reason why car owners hold this belief is the fundamental attribution error (Jones & Harris, 1967), the tendency to overemphasize the personality traits of another actor (i.e. the mood of the inspector) and underemphasize objective situational factors (the condition of the car) to explain that actor's behavior (failing a car). That such belief is limited to car owners with more frequent (potential) ego-threatening experiences of failures suggests that this error has a self-serving component. Only when it benefits the car owner to believe that other factors apart from car quality affects the inspection results does he/she admit to such belief.[16]

[15] Despite only a small minority believing that weekday or weather matters, there is suggestive evidence of higher order beliefs about *other* car owners believing these factors matter. When asked whether there are car owners in Sweden who try to increase the chance of their car passing the inspection by taking into account weekday or weather, the percentages who answer "yes, some" are higher than those admitting own belief at 52% and 44% respectively.

[16] Empirical findings from psychology support the asymmetry whereby individuals accept responsibility for positive behavioural outcomes and deny responsibility for negative outcomes (Bradley, 1978). This is also true for belief formation: subjects are more likely to respect signal strength and adhere to Bayes' rule following positive feedback while negative feedback is discounted or ignored (Eil & Rao, 2011).

5. Data

5.1 Inspection data

Our Swedish inspection dataset comes from the Swedish Transport Agency and contains a subset of all vehicle inspections conducted during the period January 2016 – December 2017.[17] We focus on regular inspections of private cars conducted on weekdays, which give us a total of 5,819,509 observations.[18][19]

The dataset contains variables about the inspection itself as well as car characteristics. Inspection variables consist of the inspection date, mileage (in km) at inspection date, expiry date, last inspection date, mileage at last inspection date, and the inspection station. Car characteristics include its registration number, registration date, last sale date, make, model, year, weight, fuel type, whether or not it is listed, and the owner's gender. A *green* dummy variable is created which equals 1 for cars whose main fuel type is one of the following considered to be green according to the Swedish Transport Agency: electric, ethanol, LPG, natural gas, methane gas, steam, biodiesel.

There is no variable containing the result of the inspection. We therefore construct the dummy variable *fail* based on the period between inspection date and expiry date. The details are provided in the appendix. We classify inspections with period less than 64 days between the inspection date and expiry date as fails and otherwise as passes.[20]

To check if car owners choose an inspection day because they expect the mood effect, it is important to exclude the possibility that car owners procrastinate and the inspection date

[17] Communication with the Swedish Transport Agency revealed that our raw dataset only captures the last inspection of a vehicle in any given month. While we have no reason to suspect that the missing inspections are correlated with any of our mood sources, we attempt to address this issue by i) identifying the missing observations using available data on previous inspection and ii) obtaining a separate dataset with fewer control variables but which contains all inspections. The analysis is provided in the appendix, showing that our results are qualitatively unchanged.

[18] We exclude non-regular inspections, such as re-inspections, inspections when a vehicle is newly registered, or spot checks. Private cars are defined as vehicles owned by a private person, classified as type *"personbil"*, used privately, and not for lease.

[19] Our raw microdata, obtained from Vägtrafikregistret (the road traffic registry, a section of the Swedish Transport Agency), shows some discrepancy when compared with the aggregated summary statistics published by the Swedish Transport Agency: for regular inspections of vehicles classified as *"personbil"*, we have 3,163,019 and 3,209,166 observations in 2016 and 2017 with 16% failure rate in each year while the published figures by the Swedish Transport Agency are 3,688,270 and 3,738,057 with 26% failure rate in each year. We have unfortunately been unable to obtain the raw data that forms the basis of the published figure, but suspect that the discrepancy is due to two reasons. First, as noted in Footnote 17 above, some inspections are not recorded in the register data. If a car fails a regular inspection and is re-inspected in the same month, the original dataset misses the first (regular) inspection leading to fewer regular inspections with lower average failure rate. We address this issue in the appendix though we have no reason to suspect that the missing observations affect our analysis of mood effect on failure rates. Second is the exclusion of *"näringsidkare"* (business owners), which is an additional owner-category shown separately in another report by the Swedish government agency for transport policy analysis and Statistics Sweden, with much older cars and likely higher failure rates. The number of company-owned cars in our dataset is indeed fewer than that given in the forenamed report. Given that we exclude cars owned by organizations in our analysis, these missing observations will not affect our conclusions.

[20] In short, the number 64 was chosen by assuming all inspections requiring the car to return within 35 days to be fails, assuming inspections where the car does not need to return for at least another 150 days to be passes, and doing spot checks of the results for the remaining inspections on a third-party website. Details are available in the appendix.

chosen is simply the last possible date according to the fixed inspection periods. Only 2.86% of all inspections were conducted on the last day of the five-month inspection period. Therefore, the vast majority of inspection dates are chosen for reasons other than that it is the last possible day.

Our English inspection dataset comes from the UK Department of Transport and is publicly available.[21] We use data from January 2016 – December 2017 and focus on regular inspections of cars and similar vehicles conducted on weekdays, giving us a total of 41,529,843 observations.[22] The dataset contains inspection variables including the inspection date, mileage (in miles, which we have converted to km) at inspection date, postcode area of inspection station, and the inspection result. Car characteristics include its vehicle ID number, registration date, fuel type, and make. We construct the age variable equal to the period between inspection date and registration date, and the dummy variable *green* equal to 1 if the car's fuel type is one of the following: compressed natural gas, electric diesel, electric, hybrid electric, liquefied natural gas or steam.

A summary of the descriptive statistics, for variables used in the analysis, are presented in Table 2.[23] The average inspected car in Sweden has around 156,000 km in mileage. A small number run on green fuels. Overall, 16% of inspections result in failure. The average inspected car in England has lower mileage than in Sweden, it has travelled 121,000 km. Green cars are more common at 0.6%. The differences between the average inspected car in England and Sweden depend partly on different legislations. In Sweden new cars only have to be inspected two times before the car turns five years old, in England the corresponding number of inspections is three.

Table 2 Descriptive statistics of inspection data

Variable	N	Mean	SD	Min	Max
SWEDEN					
Kilometer	5,806,925	155.72	87.88	0.001	999.99
Green	5,819,509	0.0008	0.0288	0	1
Fail	5,819,509	0.1595	0.3662	0	1
Good weather	5,441,091	0.4106	0.4919	0	1
Unexpected win	5,819,509	0.0016	0.0404	0	1
ENGLAND					
Kilometer	41,402,699	121.36	75.83	0.0016	1,609.34
Green	41,529,843	0.0060	0.0772	0	1

[21] https://data.gov.uk/dataset/e3939ef8-30c7-4ca8-9c7c-ad9475cc9b2f/anonymised-mot-tests-and-results, accessed 2019-05-16.

[22] The smallest classification of vehicle type is test class. We keep vehicles whose test class is 4, which includes cars but also other vehicles with up to eight passenger seats and some passenger vehicles with 9-12 passenger seats.

[23] While we have data on the car's age, we have chosen not to include it in the analysis since age is highly correlated with mileage (the correlation is 34% in Sweden and 42% in England), which is a better proxy for the car's quality. For example, there are many vintage cars which are old and yet are kept in good condition by the owners. As a robustness check we conduct regressions controlling for age, the results are qualitatively unchanged and shown in the appendix.

Fail	41,529,843	0.2660	0.4419	0	1
Good weather	20,911,495	0.6584	0.4742	0	1
Unexpected win	41,529,843	0.0007	0.0238	0	1

Kilometer: mileage of car in '000 km. *Age*: age of car in years. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Fail*: dummy variable which equals 1 if the inspection results in a fail. *Good weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly.

5.2 Weather data

For Sweden, we use daily cloud cover as our mood proxy as is done in previous studies (Goetzmann et al., 2015; Hirshleifer & Shumway, 2003). Our data comes from the Swedish Meteorological and Hydrological Institute (SMHI) and is published on the website for Sveby, a development program run by the construction and real estate industry.[24] The dataset contains hourly cloud cover for each of the 310 towns and municipalities around Sweden for 2016-2017. We use the average hourly cloud cover between 6am to 6pm for each day as our weather indicator, measured in octa where 0 octa indicates a clear sky and 8 octa indicates a completely overcast sky. Using this value to measure the amount of sunlight inspectors are exposed to thus assumes that cloud cover does not vary too much over a given day.

Before matching weather data with the inspection site, we generate a variable indicating the town or municipality of each inspection station from the station's name, which is typically given by the company name followed by the town or municipality. We are thus able to match 93.5% of the observations. We deseasonalise the weather data by averaging the cloud cover for a particular week for each station and taking the difference between the actual cloud cover and the weekly average. We then generate the dummy variable *good weather* which equals 1 if the deseasonalised cloud cover is negative, that is, if the day has lower cloud cover than the average for that week and location. As indicated in Table 2, around 41% of inspections are conducted on "good weather" days.

There is no available cloud cover data for England and we have therefore used a dataset on rainfall obtained from the Met Office as our mood proxy, hypothesizing that rainfall is likely to be correlated with cloud cover and therefore bad mood (Meier et al., 2019; Schwarz & Clore, 1983).[25] The dataset contains total daily precipitation amount (in mm) measured between 9am and 9am the day after, for each 5km x 5km grid covering the whole country, for the year 2016. These grid coordinates are then matched to another dataset containing postcodes and grid references for all UK cities, towns and villages.[26] Finally, this dataset is merged with the inspection dataset using the postcode area of the inspection station. We are able to match 88 postcode areas out of 99, corresponding to 92.96% of all 2016 observations, giving us 20,911,495 observations. We deseasonalise the weather data by averaging the rainfall for a particular week for each postcode area and taking the difference between the actual rainfall and

[24] SMHI's website only publishes cloud cover data for 111 weather stations around Sweden for our period of analysis (http://smhi.org). In contrast, Sveby's website publishes data, also provided by SMHI, for 310 locations (http://www.sveby.org).
[25] https://catalogue.ceda.ac.uk/uuid/319b3f878c7d4cbfbdb356e19d8061d6, accessed 2019-05-16.
[26] https://www.townslist.co.uk/, accessed 2019-05-16.

the weekly average. We then generate the dummy variable *good weather* which equals 1 if the deseasonalised rainfall is negative, that is, if the day has lower rainfall than the average for that week and location. As indicated in Table 2, around 66% of inspections are conducted on "good weather" days.

For comparison purposes we only use the 2016 Swedish data, totaling 2,702,192 observations.

5.3 Sports data

We use unexpected wins from the national soccer league in both Sweden and England as our third mood proxy.[27] Results and odds from the Swedish top league Allsvenskan in 2016 and 2017 are publicly available and we focus on the 14 cities with unique teams.[28] These results are matched with the inspection data using the city in which the inspection station is located. We create a dummy variable *unexpected win* which is equal to 1 for inspections conducted in one of these 14 cities on the day after the local team won a match when it was unexpected, which is true when the odds of winning were higher than the odds of losing. As indicated in Table 2, unexpected local victories affect around 0.2% of inspections (9,501 observations).

Results and odds from the English premier league during 2016 and 2017 are also publicly available and we have similarly focused on 13 cities with unique teams.[29] These results are matched with the inspection data using the postcode area in which the inspection station is located. The dummy variable *unexpected win* is created in a similar way. Around 0.07% of inspections (23,627 observations) are conducted in postcode areas whose local team won a match unexpectedly.

6. Results

Our results section is divided into subsections, each of which deals with mood effect from a particular type of day, in decreasing order of predictability. Given the belief that mood effects exist, as demonstrated in the existing literature as well as our survey, car owners may strategically target days on which mood is predicted to have an effect on inspectors. This is easily done for Friday, which occurs every week. Hence, there may be a selection bias that also plays a role in the inspection result, on top of any mood effect. Although we have a large set of control variables, we cannot exclude the possibility that selection bias through unobservable characteristics affects failure rate, which is why we seek to minimize this. Fortunately, certain types of days when people are expected to be in a good mood are less likely to be predicted in advance. For example, sunny days are more difficult to target since weather forecast may not be perfectly accurate. Similarly, it is not always possible for a car owner to target an inspector in a good mood after the local soccer team won when it was predicted to lose. On these types

[27] We have focused on unexpected wins to give mood the highest possibility of affecting inspection results. Our results are qualitatively unchanged when we use *win*, which is equal to 1 for inspections conducted on days after the local team won a match regardless of odds. The results are available in the appendix together with other robustness checks using match days, losses, and unexpected losses.

[28] http://www.football-data.co.uk/sweden.php, accessed 2019-12-10.

[29] http://www.football-data.co.uk/england.php, accessed 2019-12-10.

of days, selection effect should be less of a concern and we should be better able to detect any mood effect.[30]

Each subsection presents the distribution of inspections, the failure rate and quality of cars across different days. These are followed by regression results. Columns (1)-(3) of the regression table investigate *mood effect*: the effect of choosing a particular day on the likelihood of failing the inspection. Columns (4)-(5) investigate *selection effect*: the effect of car quality, as indicated by mileage, on the owner's likelihood of choosing a particular day. We include the inspection year to control for any time trend. The information on car characteristics also allows us to control for other variables such as whether its main fuel type is classified as *green* and the make of the car. As per Bennett et al. (2013) we use linear probability models with robust standard errors. With the large number of observations, this model closely approximates logistic regressions.[31] We use fixed-effects for station location, as indicated by the city or town in Sweden and postcode area in England, to address concerns that area specific effects, such as income, correlate with car quality. We cluster standard errors at the same geographical level. Given our high number of observations, we adopt a stricter threshold for significance: * denotes $p<0.05$, ** denotes $p<0.01$, and *** denotes $p<0.005$ (Benjamin et al., 2018).

Table 3 presents a summary of our results. The first row shows the effect of choosing a particular day on failure rate, as given in column (3) in subsequent tables. These coefficients indicate the presence of any mood effect: whether failure rate is lower on days when inspectors are predicted to be in a good mood, after controlling for car quality and other variables. Note that according to the mood effect hypothesis these coefficients should be negative: good mood days should be associated with lower failure rates. The second row is the effect of mileage on the car owners' likelihood of choosing a particular day for inspection, as given in column (5) in subsequent regression tables. These coefficients indicate the presence of selection bias: whether car owners strategically select days when inspectors are predicted to be in a good mood. According to our prediction, these coefficients should be positive: lower quality cars with higher mileage should be more likely to select into good mood days. These effects are expected to be more pronounced in Sweden than England, and on Friday, the good mood day that is easiest to predict, and less so for good weather days and days following sports wins.

Starting from the Friday column, we see that higher mileage cars are more likely to be inspected on a Friday, which is a day when inspectors are predicted to be in a good mood and which is also relatively easy to target. Failure rate in Sweden is found to be higher on these days, even after controlling for car quality, suggesting that there are other unobservable characteristics of the inspected cars that correlate with the lower quality.[32] However, failure rate in England is lower despite the lower quality, supporting the mood effect hypothesis. As we move to the right of the table, good mood days are fewer or more difficult to target, and the quality bias decreases in magnitude and significance, as expected. No mood effect is observed

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[30] Note that car owners can also inspect their cars using a drop-in service. While we do not have data on which inspections are drop-in or pre-booked, we argue that Friday inspections are easier to plan in advance than inspections on a good weather day or following a sports win, even for a drop-in service. Thus the selection effect should be greater for Friday than the other two good mood days.

[31] Our results are robust to using logistic regressions. The details are provided in the appendix.

[32] Another possible explanation is that inspectors anticipate that owners of low quality cars target good mood days, and as a result inspectors become more vigilant and stricter in their inspections. However, given that mood is diffuse and hard to detect, it is doubtful that inspectors display such higher-level thinking.

on sunny days in Sweden, while days with lower than average rainfall have higher failure rates in England. On days following the local soccer team's unexpected wins, the selection effect is, as expected, not significant. No mood effect is observed in either Sweden nor England.

Table 3 Summary of regression results

	Friday	Good weather	Unexpected win
SWEDEN			
(1) Mood effect on fail	0.00775***	-0.00103	0.00897
(2) Selection effect (Km)	7.92e-05***	-3.12e-05***	-2.15e-07
Obs.	5,806,925	2,695,306	5,806,925
ENGLAND			
(1) Mood effect on fail	-0.0136***	0.00269***	0.00415
(2) Selection effect (Km)	3.00e-05***	-9.34e-06***	-7.67e-09
Obs.	41,402,699	20,844,258	41,402,699

Row (1): Coefficients from OLS regressions of likelihood of failing inspection on mood source as given by column title. Row (2): Coefficients from OLS regressions of likelihood of choosing for inspection the day given by the column title on Km. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Km*: mileage of car in '000 km. All regressions control for km ('000), inspection year (except for "Good weather" column which only includes 2016 data), green fuel, car make, with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

In summary, looking across the different types of days when inspectors' mood is predicted to impact inspection results, the only setting in which the results are as predicted and highly significant is confined to Fridays in England, where the mood effect amounts to 5.11% of the average failure rate. The effect size found is in the ballpark of those found in the literature on mood effect on behavior. Studies of the weather effect in financial markets, for example, find that cloud cover reduces optimism as measured by the investor's buy-sell imbalance by 2.4% (Goetzmann et al., 2015) and decreases the likelihood of a positive market return by 1.7% (Hirshleifer & Shumway, 2003). Similarly, Dehaan et al. (2017) find that cloud cover decreases analyst activity by 4.01%. Meier et al. (2019) find that rainfall decreases the likelihood of voting for political change by 2.62%, while Kaustia & Rantapuska (2016) find a Friday effect of 3.47% on the buy-sell imbalance of individual traders. No evidence of mood effect is detected in our Swedish data. Hence, although there exist beliefs about mood effect in the context of car inspections in Sweden, the actual effect is much less common than what these beliefs and the existing literature on mood effect would predict.

6.1 Mood effect on Fridays

We start our investigation of the mood effect with Friday, the day that is easiest for car owners to strategically target.[33]

The distribution of inspection days for Sweden and England are given in Table 4. For both countries, the distribution is significantly different from uniform (χ^2-test, p<0.001), with slightly more owners choosing Tuesday and Wednesday than other weekdays.

Table 4 Frequency of inspections by weekday

Day	% Sweden	% England
Mon (1)	19.57	19.60
Tue (2)	20.36	21.03
Wed (3)	20.28	20.39
Thu (4)	19.89	19.77
Fri (5)	19.90	19.22

If inspectors are prone to the mood effect, fail rates are expected to be lower on Friday compared to other days. As shown in Figure 1, this is indeed the case for England. Failure rate is lower on Friday compared to other days by 1.3 percentage points (t-test, p<0.001). However, the opposite holds for Sweden. Failure rate is higher, also by 1.3 percentage points, on Friday compared to other days (t-test, p<0.001). One reason for the higher failure rate could be the lower average quality of Swedish cars submitted for inspection. As shown in Figure 1, there is indeed a clear spike in the car's mileage on Friday in Sweden, but surprisingly also in England. Swedish cars submitted on Fridays have been driven an extra 3,836 km, (t-test, p<0.001) while English cars have an extra 1,132 km (t-test, p<0.001). Given the widely held expectation that mood is best on Friday, a car owner who drives often, and whose car thus has a higher mileage, will have more incentive to take advantage of mood effect since failure will put their car out of use for some time. It appears that owners of low quality cars do selectively target Fridays for inspection, potentially resulting in the higher failure rate observed in Sweden. For England, however, the fact that failure rate is lower on Friday despite the lower quality of cars points to inspectors' mood as a potential influence on decisions.

[33] In the appendix we provide robustness checks using Monday, which is predicted to be a bad mood day, and all days of the week.

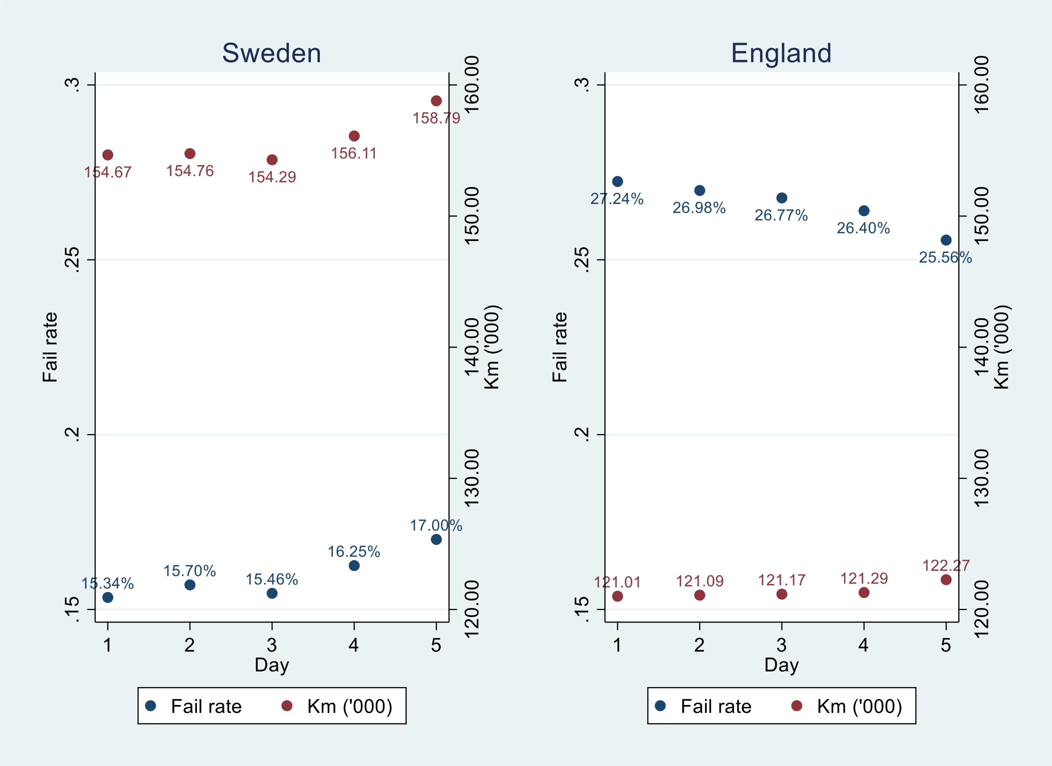

Figure 1 Failure rate and car quality by weekday

We next regress inspectors' decision to fail or pass the car on the Friday dummy variable. Our results in column (1) of Table 5 confirm our earlier finding about Sweden. Failure rate is higher on Friday than other weekdays by about 1.3 percentage points. Given that the cars that are inspected on Friday are of lower quality compared to other days, it is not surprising that inspectors fail more cars on Friday. However, inspectors may still display the mood effect if they have a lower likelihood of failing a car on a Friday, controlling for the car quality. We check for this possibility in the regression in column (2). Our results indicate that kilometer does increase the likelihood of failure, but they do not fully explain the Friday effect on failure rate, which is still higher by 0.8 percentage points compared to other days. After controlling for all other car characteristics in column (3) inspections are still 0.8 percentage points more likely to result in a fail on Fridays. While this may seem small, considering that on average 2.9 million cars are inspected annually, the Friday effect corresponds to over 20,000 cars per year. The residual Friday effect suggests that there may be other car characteristics that indicate low quality that are not captured in our data. Owners of these low quality cars choose to inspect their cars on Fridays, thus contributing to the higher failure rate.

Table 5 Regression results for Fridays in Sweden

	(1) Fail	(2) Fail	(3) Fail	(4) Fri	(5) Fri
Friday	0.0125***	0.00765***	0.00775***		
	(0.000575)	(0.000510)	(0.000502)		
Kilometer		0.00122***	0.00132***	8.48e-05***	7.92e-05***

		(1.56e-05)	(1.77e-05)	(2.91e-06)	(2.88e-06)
Inspection year			-0.00128		0.00424***
			(0.000971)		(0.000739)
Green			0.00698		0.0130*
			(0.00532)		(0.00581)
Constant	0.157***	-0.0316***	-0.00888***	0.186***	0.196***
	(0.000114)	(0.00242)	(0.00242)	(0.000453)	(0.000780)
Make			X		X
Area FE	X	X	X	X	X
Observations	5,819,509	5,806,925	5,806,925	5,806,925	5,806,925
R-squared	0.007	0.089	0.100	0.002	0.003

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing Friday for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

We next regress the choice of car owners to inspect on Friday on our proxies of car quality, mileage. The results in column (4) confirm our earlier finding that the lower the car quality, the higher the likelihood of the owner choosing a Friday inspection. The effects are relatively small, however. An extra 100,000 km traveled increases the likelihood of choosing Friday by 0.8 percentage points. We find similar effects when controlling for other car characteristics and makes in column (5). These results provide some evidence that car owners do act on their expectation of the mood effect, even when it is in fact unsupported. Owners of low quality cars expect to be treated more leniently and are more likely to inspect on a Friday than other weekdays. Another potential explanation is that owners of low quality cars, who expect a high likelihood of failure, choose to postpone the inspection to the last working day of the week since they want to keep using their car for work.

In Table 6 we present the regression results for England. In columns (1)-(3), we see that failure rate is lower on Fridays, consistent with our findings above. This is true even when controlling for the lower quality of cars, as proxied by mileage. This finding indicates the presence of mood effect in inspectors who are in a good mood as they anticipate the weekend. The fact that legal differences allow inspectors to also perform repair and thus increase the incentives to fail may also potentially play a role as there is 'more room' to be lenient, as compared to Sweden where failure rates are in general lower. We find that failure rate is lower in 2017 and for green cars. In columns (4)-(5) we confirm the selection effect: higher mileage cars are more likely to be inspected on Fridays, though the effect is smaller than in Sweden. One possible reason is the five-month inspection window in Sweden which is longer compared to England, where owners have a one-month window to inspect without affecting the renewal date. There is thus a smaller possibility to target Friday inspections in England.

Table 6 Regression results for Fridays in England

	(1)	(2)	(3)	(4)	(5)
	Fail	Fail	Fail	Fri	Fri

Friday	-0.0123***	-0.0137***	-0.0136***		
	(0.000409)	(0.000483)	(0.000475)		
Kilometer		0.00124***	0.00127***	3.22e-05***	3.00e-05***
		(4.01e-05)	(4.05e-05)	(3.19e-06)	(3.13e-06)
Inspection year			-0.00565***		0.00166***
			(0.000456)		(0.000130)
Green			-0.0733***		-0.00452*
			(0.00341)		(0.00203)
Constant	0.268***	0.117***	0.227***	0.188***	0.188***
	(7.85e-05)	(0.00480)	(0.00442)	(0.000387)	(0.000606)
Make			X		X
Area FE	X	X	X	X	X
Observations	41,529,843	41,402,699	41,402,699	41,402,699	41,402,699
R-squared	0.010	0.055	0.065	0.000	0.000

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing Friday for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

6.2 Mood effect on good weather days

Fridays can be strategically targeted by owners of low quality cars, thus potentially creating a quality selection bias which will affect the failure rate on these days. One exogenous factor that has been argued to affect mood is the weather. As is also demonstrated in our survey, mood is predicted to be best on a sunny day. We investigate whether mood has any effect on failure rate when car owners can no longer perfectly predict this in advance and strategically submit their low quality cars to be inspected on good weather days: days which are less cloudy than average in Sweden, or less rainy than average in England.[34]

Figure 2 plots the distribution of our measure of deseasonalised cloud cover in Sweden and deseasonalised rainfall in England. As expected, the majority of observations are concentrated around 0, with very few extreme observations.

[34] In the appendix we provide robustness checks using non-deseasonalised weather data and continuous deseasonalised weather data.

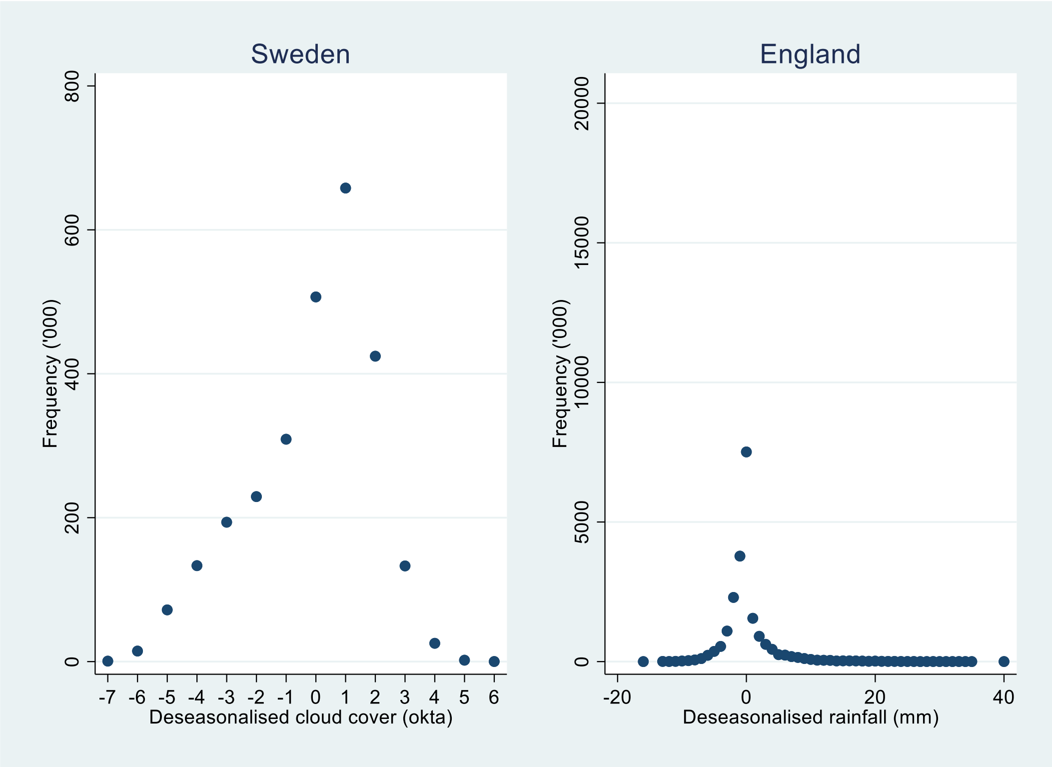

Figure 2 Distribution of deseasonalised cloud cover and rainfall, negative values indicate days in Sweden (England) which are sunnier (less rainy) than the average for that week and geographical location

Figure 3 plots the trend in failure rate across weather conditions. Overall, there is little support for the mood effect, under which failure rate should be monotonically increasing with deseasonalised cloud cover or rainfall. In Sweden, for the vast majority of observations within the range of -3 to +3 octas, there is no monotonic trend in failure rate: it increases with cloud cover and then decreases. Comparing failure rates using the variable *good weather*, we find that failure rate is significantly lower on good weather days, but the effect is small (16.0% vs 16.4%, t-test, $p<0.001$) and this is most likely to be driven by the high failure rate on extremely cloudy days. In England we do not observe any obvious trend in failure rate either, looking at the center of the graph where the majority of observations are concentrated. Failure rates are found to be slightly higher on good weather days (27.42% vs 27.19%, t-test, $p<0.001$). However, this is likely to be driven by the high variability in failure rates on days with extremely high rainfall.

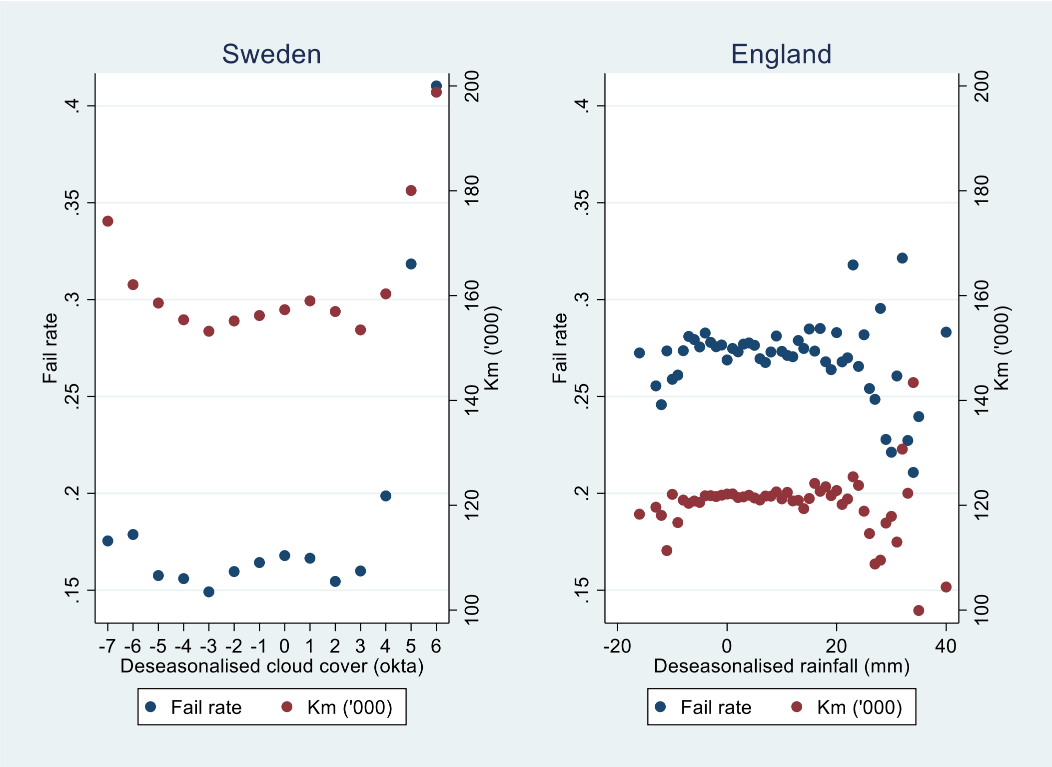

Figure 3 Failure rate and car quality by deseasonalised cloud cover and rainfall

Figure 3 also plots the quality of cars against our weather variables. There is no monotonic trend in car quality over cloud cover or rainfall either. In Sweden, cars have on average slightly lower mileage on good weather days (155.70 tkm vs 157.79 tkm, t-test, $p<0.001$), as is also the case in England (121.85 tkm vs 121.92 tkm, t-test, $p=0.0395$). However, it is clear from the graph that the trend in failure rate closely follows that of mileage in both Sweden and England. Overall, the lack of clear trend suggests that it is more difficult for car owners to specifically target good weather days for inspecting low quality cars.

Regression results for good weather in Sweden, using deseasonalised cloud cover, are presented in Table 7. Columns (1)-(3) show the effect of cloud cover on failure rate. Confirming our findings above, inspecting on days with lower than average cloud cover has no significant effect on failure rate. The lack of evidence for mood effect as proxied by weather reflects the difficulty in using weather as a proxy for mood. Cloud cover may vary throughout the day while at the same time differences in cloud cover may be difficult to be noticed by inspectors to sufficiently affect mood.[35] This is consistent with Kaustia & Rantapuska (2016) who also do not find any significant effect of cloud cover on trading activity, arguing that there may not be sufficient variation in weather to influence mood and hence behavior. In columns (4)-(5) we regress the deseasonalised cloud cover of inspection days on car characteristics. Car quality appears to be better on sunny days, perhaps because owners who look after their cars prefer to avoid driving in bad weather conditions. However, the overall size of the selection effect is also much smaller than that on Fridays, which is not surprising since good weather days are not as easy as Fridays to target.

[35] Robustness checks without the deseasonalisation procedure give qualitatively the same results. The results are provided in the appendix.

Table 7 Regression results for deseasonalised cloud cover in Sweden

	(1) Fail	(2) Fail	(3) Fail	(4) Good weather	(5) Good weather
Good weather	-0.00222*	-0.000876	-0.00103		
	(0.000967)	(0.000856)	(0.000849)		
Kilometer		0.00123***	0.00133***	-3.65e-05***	-3.12e-05***
		(1.67e-05)	(1.90e-05)	(4.87e-06)	(5.01e-06)
Green			0.00933		0.0165*
			(0.00773)		(0.00837)
Constant	0.163***	-0.0304***	-0.00699**	0.435***	0.447***
	(0.000416)	(0.00271)	(0.00268)	(0.000764)	(0.00131)
Make			X		X
Area FE	X	X	X	X	X
Observations	2,702,192	2,695,306	2,695,306	2,695,306	2,695,306
R-squared	0.007	0.091	0.101	0.005	0.005

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing good weather days for inspection. *Good weather*: dummy variable which equals 1 if the car is inspected on a day whose deseasonalised cloud cover is negative. *Kilometer*: mileage of car in ‘000 km. *Date*: inspection date. *Green*: dummy variable which equals 1 if the car’s main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

Table 8 presents the regression results for England. Good weather affects the likelihood of failure, but not in the predicted direction. Inspecting on a day which is less rainy than average increases failure rate by 0.2 percentage points, corresponding to around 0.91% of the average failure rate in England. While the effect is small relative to the Friday effect, it is surprising since the average quality of the car, as shown in the coefficients for kilometer in columns (4) and (5), is in fact better than on rainier days as is also the case in Sweden. One possible explanation is that inspectors have a higher opportunity cost for working indoor on a good weather day and their mood is in fact made worse the nicer the weather. As expected, the selection effect is much smaller than that found on Fridays.

Table 8 Regression results for deseasonalised rainfall in England

	(1) Fail	(2) Fail	(3) Fail	(4) Good weather	(5) Good weather
Good weather	0.00236***	0.00264***	0.00269***		
	(0.000240)	(0.000240)	(0.000237)		
Kilometer		0.00128***	0.00131***	-9.35e-06***	-9.34e-06***
		(4.08e-05)	(4.11e-05)	(1.86e-06)	(1.79e-06)
Green			-0.0699***		-0.000534
			(0.00385)		(0.00188)
Constant	0.272***	0.115***	0.224***	0.660***	0.659***
	(0.000158)	(0.00503)	(0.00470)	(0.000226)	(0.000515)
Make			X		X

Area FE	X	X	X	X	X
Observations	20,911,495	20,844,258	20,844,258	20,844,258	20,844,258
R-squared	0.010	0.056	0.066	0.002	0.002

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing good weather days for inspection. *Good weather*: dummy variable which equals 1 if the car is inspected on a day whose deseasonalised rainfall is negative. *Kilometer*: mileage of car in '000 km. *Date*: inspection date. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

6.3 Mood effect after unexpected wins

Another potential day for inspectors to display good mood which is unpredictable for car owners is after important sports results. Card & Dahl (2011) study the link between domestic partner violence and professional football match results, finding that upset losses lead to a 10% increase in the rate of domestic violence. The authors argue that major sports results can generate emotional cues or visceral factors reflecting gain-loss utility around a reference point, in particular when that win or loss is highly unexpected. This reasoning motivates our investigation of failure rate and car owners' behavior on days following unexpected wins by the local soccer team, which are predicted to induce good mood in inspectors. As a reminder, we use the results of soccer matches for cities or towns who have a unique team in the top national league, and create the dummy variable *unexpected win* which equals 1 for inspections conducted in that city on days after a win when the odds for winning were higher than the odds for losing.

In Sweden, failure rates are slightly higher after an unexpected win than other days (17.2% vs 16.0%, t-test, p=0.0007). Car quality is also better on days after wins (152 tkm vs 156 tkm, t-test, p<0.001) though is unlikely to be due to conscious targeting on the part of car owners. In England, failure rates after unexpected wins are higher (28.9% vs 26.60%, t-test, p<0.001), although mileage is lower (119 tkm vs 121 tkm, t-test, p<0.0001).

Regression results for days after unexpected wins in Sweden are presented in Table 9. There is no evidence of mood effect stemming from the local soccer team winning, as shown by the insignificant coefficients of *unexpected win* in columns (1)-(3). Columns (4)-(5) show that there is no selection bias in kilometer on win days either. This is not surprising given that win days are nearly impossible to predict in advance for owners of low quality cars who wish to target these days.

Table 9 Regression results for days after unexpected wins in Sweden

	(1) Fail	(2) Fail	(3) Fail	(4) Unexpected win	(5) Unexpected win
Unexpexted win	0.00843	0.00948	0.00897		
	(0.00928)	(0.00823)	(0.00813)		
Kilometer		0.00122***	0.00132***	-2.47e-07	-2.15e-07
		(1.56e-05)	(1.77e-05)	(2.71e-07)	(2.76e-07)

Inspection year			-0.00124		-0.000339
			(0.000973)		(0.000604)
Green			0.00708		-0.000215
			(0.00532)		(0.000513)
Constant	0.160***	-0.0302***	-0.00738***	0.00167***	0.00193***
	(1.52e-05)	(0.00242)	(0.00241)	(4.22e-05)	(0.000343)
Make			X		X
Area FE	X	X	X	X	X
Observations	5,819,509	5,806,925	5,806,925	5,806,925	5,806,925
R-squared	0.007	0.089	0.100	0.010	0.010

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing unexpected win days for inspection. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Date*: inspection date. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

Table 10 presents the regression results for win days in England. As noted previously, failure rates are surprisingly higher on these days even though inspectors are predicted to be in a good mood. The effect amounts to roughly 2.01% of the average failure rate. Inspectors may have been celebrating late into the night and show up to work tired, thus erasing any potential good mood effect. The fact that this effect is not found in Sweden could be due to soccer being more popular in England. Selection bias, as captured by the coefficients for kilometer in columns (4)-(5), are as predicted insignificant.

Table 10 Regression results for days after unexpected wins in England

	(1) Fail	(2) Fail	(3) Fail	(4) Unexpexted win	(5) Unexpexted win
Unexpexted win	0.00445	0.00466	0.00415		
	(0.00424)	(0.00465)	(0.00402)		
Kilometer		0.00124***	0.00127***	-7.06e-09	-7.67e-09
		(4.01e-05)	(4.05e-05)	(1.05e-07)	(1.10e-07)
Inspection year			-0.00568***		-0.000127
			(0.000455)		(0.000246)
Green			-0.0732***		2.52e-05
			(0.00340)		(1.53e-05)
Constant	0.266***	0.114***	0.224***	0.000570***	0.000627***
	(2.41e-06)	(0.00487)	(0.00447)	(1.27e-05)	(0.000118)
Make			X		X
Area FE		X	X	X	X
Observations	41,529,843	41,402,699	41,402,699	41,402,699	41,402,699
R-squared	0.010	0.055	0.065	0.005	0.005

Columns (1)-(3): OLS regressions of likelihood of failing inspection. Columns (4)-(5): OLS regressions of likelihood of choosing unexpected win days for inspection. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km.

Date: inspection date. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Make* includes twenty dummy variables for the twenty most popular makes of cars. Robust standard errors in parentheses, *** p<0.005, ** p<0.01, * p<0.5.

6.4 Bad mood effects

Our data also allows an analysis of bad mood effects whereby failure rates are hypothesized to be higher on days when inspectors' mood is predicted to be bad, namely on Mondays, bad weather days and days following unexpected sports losses. Card & Dahl (2011), for example, find that unexpected losses by professional football teams are associated with a significant increase in domestic violence. We therefore repeat our analysis and report the results in this subsection.

We create a dummy variable Monday which equals to 1 for inspections conducted on Mondays and 0 otherwise. For bad weather, we again use the deseasonalised weather data and generate a dummy *bad weather* which equals 1 if the deseasonalised cloud cover in Sweden or rainfall in England is positive, that is, if the day has higher cloud cover or rainfall than the average for that week and location.[36] Around 58.9% of inspections in Sweden and 33.5% in England are conducted on *bad weather* days. Finally, we create a dummy variable *unexpected loss* which is equal to 1 for inspections conducted on the day after the local team lost a match when it is unexpected, that is when the odds of losing are higher than the odds of winning. Unexpected losses affect 7,599 inspections (0.13% of total) in Sweden and 16,546 (0.04%) in England.

Table 11 presents a summary of the regression results for bad mood days, the full results are provided in the appendix. If inspectors fail more cars on bad mood days, the mood coefficients in row (1) should be positive and significant. This is found true only in two of the six cases considered: on Mondays and following unexpected losses in England, when failure rates are higher by around 0.8% (effect size of 3% relative to the English average failure rate). For bad weather days and following unexpected losses in Sweden, no effect is found, while in the remaining two cases effects are found in the opposite direction.

We find more consistent support for the selection effect hypothesis, whereby rational owners of low quality cars with high mileage avoid bad mood days. The coefficients of *Km* in row (2) are negative and significant for Mondays, the bad mood day that is easiest to avoid. The magnitudes are however smaller than those found on good mood days. Surprisingly, higher mileage cars are found to be more likely to select into inspections on bad weather days, however these bad mood days are more difficult to avoid and these effects are unlikely to be conscious actions by car owners. As expected, no selection effect is observed following unexpected losses.

Table 11 Summary of regression results for bad mood effects

	Monday	Bad weather	Unexpected loss
SWEDEN			

[36] The dummy variable *bad weather* is not exactly equal to 1 minus *good weather* since there are a small number of observations where the deseasonalised cloud cover or rainfall is equal to zero, which were therefore neither classified as a good weather day or a bad weather day.

(1) Mood effect on fail	-0.00597***	0.00103	0.00430
(2) Selection effect (Km)	-2.43e-05***	3.14e-05***	-3.09e-07
Obs.	5,806,925	2,695,306	5,806,925
ENGLAND			
(1) Mood effect on fail	0.00812***	-0.00276***	0.00770***
(2) Selection effect (Km)	-1.03e-05***	1.16e-05***	1.80e-07
Obs.	41,402,699	20,844,258	41,402,699

Row (1): Coefficients from OLS regressions of likelihood of failing inspection on mood source as given by column title. Row (2): Coefficients from OLS regressions of likelihood of choosing for inspection the day given by the column title on Km. *Monday*: dummy variable which equals 1 if the car is inspected on a Monday. *Bad weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is positive. *Unexpected loss*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team lost unexpectedly. *Km*: mileage of car in '000 km. All regressions control for km ('000), inspection year (except for "Bad weather" column which only includes 2016 data), green fuel, car make, with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Overall, our results provide no consistent evidence of mood effect. Of the twelve cases considered (three good mood sources and three bad mood sources in two countries), only three yield effects in the predicted direction. Four effects go in the opposite direction, where good mood days are associated with higher failure rates and bad mood days with lower failure rates, while the remaining five cases are not statistically significant. While there is always an ex-post rational explanation for why we find mood effect in some cases and not in others, our study illustrates the pitfalls of selecting one particular mood source and drawing conclusions from any resulting change in behavior. More consistent selection effects are observed for easily targeted or avoided mood days: high mileage cars select into Friday inspections and avoid Monday inspections in both Sweden and England.

7. Analysis using Hirshleifer and Shumway (2003) data

One of the most highly cited studies in the literature on external proxies for mood effect is Hirshleifer & Shumway (2003), henceforth HS2003, which finds that sunniness has a positive effect on daily stock market index returns.[37] There have been critics to the research design adopted in HS2003, in particular the decision to pool data from all countries without changing the threshold significance value, thus increasing the likelihood of Type 1 error (see, for example, Kim, 2017). Our criticism of this study, along with many other studies finding that single external factors such as weather, Friday and sports results impact mood and therefore behavior, is related to the need to study mood effects in a more systematic manner, in particular by making use of multiple mood sources. Mood is diffuse and unobservable, and we propose that claims that it significantly affects behavior ought to be robust to using different sources of good mood, large dataset, and relevant controls. We use the data from HS2003, obtained from one of the authors' homepage, to investigate how robust the findings are when mood effect is

[37] The paper has been cited 1498 times according to Google Scholar, as of 2019-05-24.

systematically studied using our approach.[38] The data contains the following variables: date, average cloud cover for a particular date and location, deseasonalised cloud cover, daily return, and city. We can therefore check the effect of good mood from Friday, in addition to the good weather hypothesis proposed in the paper. Furthermore, we study the effect of sports results by compiling data on soccer matches as was done in Edmans et al (2007). The dataset includes matches from the World Cup, European Championship, Copa America and Asian Cup, as well as qualifying rounds of these tournaments where the match is considered to be "close" according to the Elo ratings of the two teams (in total 777 matches from 18 tournaments across 1982-1997).[39]

To make the analysis as comparable as possible to our analysis, we create the dummy variable *good weather* which equals 1 if the deseasonalised cloud cover is negative. We also generate the variable country, there is a one-to-one correspondence between country and the city of the stock market. In total there are 92,808 observations of daily stock market return in 26 countries from 1982 to 1997. The closest specification to our model is a regression of daily return on the good mood source, which can be Friday, good weather or sports wins, and year dummies. We control for country fixed-effects and cluster standard errors at this level.

If mood has a sufficiently strong effect on investors' sentiments, we should see positive effects on days which are predicted to induce good mood: including Fridays, good weather days, and following unexpected soccer wins. Table 12 presents the regression results for daily market index returns. In column (1) we see that Friday has no significant effect on index returns, contrary to expectations. Weather has a strong effect (column 2) which is hardly surprising since this is the result already reported in HS2003. However, sports wins are not significant (column 3). When stock returns are regressed on several mood events at the same time (column 4), only weather has any significant effect. If mood has a sufficiently strong effect on investors' sentiments, we should see a positive effect on all good mood days, not just on good weather days.

Table 12 Regression results from HS2003

	(1) Return	(2) Return	(3) Return	(4) Return
Friday	-0.00292			-0.00288
	(0.0149)			(0.0149)
Good weather		0.0364***		0.0364***
		(0.0116)		(0.0116)
Win			0.0307	0.0319
			(0.0640)	(0.0638)
Year	-0.00540*	-0.00538*	-0.00541*	-0.00538*
	(0.00252)	(0.00252)	(0.00253)	(0.00252)
Constant	10.85*	10.79*	10.86*	10.80*

[38] http://www-personal.umich.edu/~shumway/papers.dir/weather.html, accessed 2019-05-24.
[39] https://www.kaggle.com/kralmachine/football-results-from-1872-to-2018-datavisulation/data and http://www.eloratings.net/, accessed 2019-05-24.

	(5.023)	(5.018)	(5.025)	(5.020)
Observations	92,808	92,808	92,808	92,808
R-squared	0.009	0.009	0.009	0.009

Columns (1)-(5): OLS regressions of daily market index returns. *Friday*: dummy variable which equals 1 if the day of observation is a Friday. *Good weather*: dummy variable which equals 1 if the day of observation has a negative deseasonalised cloud cover. *Win*: dummy variable which equals 1 if the national soccer team won a match the previous day. *Year:* year of observation. Robust standard errors in parentheses clustered at country level, *** p<0.005, ** p<0.01, * p<0.5.

Our finding that not all good mood sources have an effect on behavior, despite the presence of weather effects, thus calls into question other studies that have only used one mood source to claim mood effect persists in the field.

8. Concluding remarks

There is increasing acceptance of the role mood plays in decision-making, as shown in the extensive literature based on mood-manipulation studies. We do not question the existence and potential importance of mood effects in behavior. However, we argue in this paper that there is limited evidence of mood effect in the field as proxied by external factors such as weather and weekday. Existing studies typically use a single mood source, thus making the findings prone to problems such as publication bias, false positives and spurious correlation. Using large datasets comprising of car inspections from two countries, we systematically investigate the extent to which mood affects decision-making on multiple days when external factors predict good mood in inspectors, and whether this is exploited by rational car owners.

We first establish that beliefs about mood effect exist in our setting using a survey of Swedish car owners. Such belief can give rise to selection bias, with low quality cars being more likely to be inspected on good mood days. We then study several sources of good mood with varying degrees of predictability: Fridays, good weather days, and days following the local soccer team’s unexpected wins. While we are able to control for car quality using our rich data on car characteristics, using the less predictable good mood days further enables us to control for the selection effect. Additionally, having multiple sources of good mood enables us to draw more robust conclusions about mood effect, should it be found in all three cases.

Overall, we find little support for consistent mood effect on inspectors’ decisions. Mood effect in the predicted direction is only found on Fridays in England, when failure rates are reduced by 5.11%. We find the opposite effect for Fridays in Sweden and good weather days in England, when the likelihood of failing is in fact higher (by 4.86%, 1.01% respectively). No mood effect is found following unexpected wins or good weather days in Sweden. Similarly inconsistent findings are obtained when analyzing bad mood days.

More consistent results are found for the selection bias hypothesis: car quality is lower on Fridays, a good mood day that is easy to target. The effect is small, however: a car needs to have been driven an extra 100,000 km for it to increase the likelihood of a Friday inspection by 0.8% in Sweden. This selection bias, together with other unobservable car characteristics related to the lower quality, may have contributed to the higher failure rate in Sweden on Fridays, overall suggesting that the selection effect is stronger than any potential mood effect. The selection effect is also confirmed on Mondays, where high mileage cars are significantly less likely to be inspected. This result highlights the importance of studying separately both sides of the market, which is typically not done in the existing mood studies using outcome variables such as stock returns which aggregate the behavior of multiple sides.

There are a number of ways to reconcile the belief of mood effect, and the observed selection bias, with the lack of clear evidence of actual mood effect. As indicated in our survey results, car owners who have previously failed inspections are the ones more likely to admit to believing that variables such as weekday and weather may affect inspection results. This suggests that car owners suffer from the fundamental attribution error (Jones & Harris, 1967), whereby inspector's decision to fail the car is attributed to inspectors' internal mood rather than external circumstances, namely the owner's car quality. Another reasoning, also related to motivated belief (see, e.g., Bénabou & Tirole, 2016), is image concerns. If having a car that passes inspection is a source of pride for the owner, believing that inspectors' mood affects inspection results can protect the owner from a loss of image when the car fails the inspection. Car owners may also have an illusion of control: they believe that they have a higher probability of passing when they have a higher degree of personal involvement (by actively choosing to inspect their cars when inspectors are expected to be in a good mood) even when this involvement is not actually relevant (Langer, 1975).

While we cannot exclude any specific mechanism and there is always an ex-post rational explanation for our results, our study points to the risks of drawing conclusions about mood effects based on only one external factor and on only one dataset. This is especially risky for a vague and collective term such as "mood" since it refers to something that is unobservable in the field and allows for many degrees of freedom when it comes to its triggers and its domain of behaviors. For instance, a researcher only focusing on our UK data and the Friday effect would most likely conclude that there is a convincing mood effect. However, our use of multiple external factors and two different datasets complicates the picture considerably.

Overall, our results show that despite apparent beliefs about mood effect, and the fact that it is taken into account by some car owners, the actual evidence for mood effect is limited. We conclude that we cannot identify mood effect with any certainty. Given the problems we outlined regarding the use of a single mood source in existing studies, our results suggest that the previous results are not representative of the full distribution of mood effects in the field. That publication bias picks out the right tail of this distribution is consistent with our findings. Given the impossibility of replication, future research on mood effect should continue to test theory-driven hypotheses that should hold if the effect indeed exists. This stresses the need for more research on the effect of mood in other field settings and using multiple mood sources and different datasets.

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Appendix

A1. Moore machine illustration of mood effect

To stress the consequences of mood effect on car inspection outcomes it is instructive to illustrate the behavior of a car inspector as a simple (Moore) machine.[40] In Figure 4 we have illustrated a car inspecting machine. The machine is initially in state q_0 (in the morning) which is not associated with any (output) behavior. The machine then gets information about the first inspected car's condition, which could be "Good" (G) or "Bad" (B). If the car's condition is "Good" the machine's transition function instructs it to move to a new state, q_P, which is associated with giving the car a "Pass". If the information about the condition is "Bad" the machine moves to another state, q_F, which is associated with giving the car a "Fail". Once the first car is inspected the machine will be in either state q_P or q_F and remain in its current state if it receives the same information it received about the first car and move to another state otherwise. Such a car inspecting machine will always react with a "Pass" or "Fail" if the information about the condition is "Good" or "Bad", respectively.

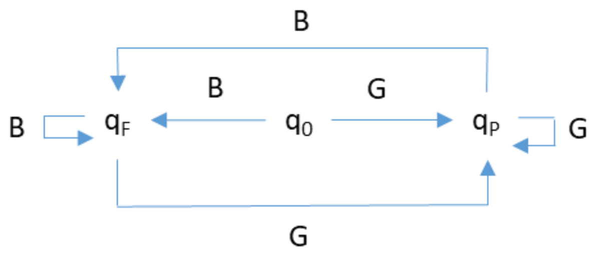

Figure 4 A car inspecting machine. q_0: initial state, q_P: state with "Pass" decision, q_F: state with "Fail" decision, G: Good condition, B: Bad condition.

Let us now consider a somewhat "moody" car inspection machine (in Figure 5) which in some subset of internal states also reacts to an irrelevant external factor, namely the weather. This machine is identical to the one in Figure 4 except for the q_F and q_{PM} states. In these states the machine reacts to both the condition of the car and the weather which could be "Rain" or "Sun". Hence, if it is rainy and the car is in bad condition (BR) the machine correctly gives the car a "Fail". However, if it is sunny (BS or GS) the machine moves to its happy mood state, q_{PM}, where it passes cars as long as the weather is sunny independent of the condition of the car. What should be clear from this very simple machine is that the causal analysis of the factors determining the machine's decisions has gotten substantially more involved since the machine now acts differently depending on the (unobservable) internal state it is in, which partly depends on irrelevant external factors. This in turn also means that the "history" of events also potentially affects the process. For instance, the machine in Figure 5 will only deviate from the one in Figure 4 when it is sunny and if the machine gets two cars in a row in bad condition. Obviously, such mood states will complicate analyses of decision-making fundamentally. In addition, the

[40] Moore machines and finite automata are classical constructs in the theory of computation (see e.g., Hopcroft & Ullman, 1979) and have been used in, e.g., game theory to represent strategies of finite complexity (see e.g. Abreu & Rubinstein, 1988).

recognition of mood states also raises the question of how they can be reconciled with the notion of rationality and preferences in economics.

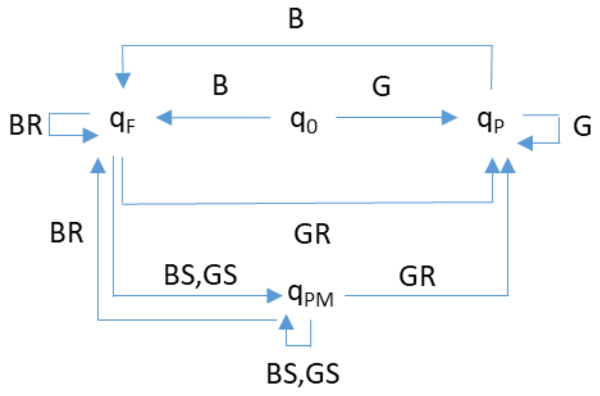

Figure 5 A car inspecting machine. q_0: initial state, q_P: state with "Pass" decision, q_F: state with "Fail" decision, q_{PM}: "happy mood" state with "Pass" decision, G: Good condition, B: Bad condition, GR: Good condition and rain, GS: Good condition and sun, BR: Bad condition and rain, BS: bad condition and sun.

A2. Fixed inspection periods prior to 18 May 2018

Table 13 Inspection period

Last digit of car registration number	Recommended month	Inspection period
1	January	November-March
2	February	December-April
3	March	January-May
4	April	February-June
5	July	May-September
6	August	June-October
7	September	July-November
8	October	August-December
9	November	September-January
0	December	October-February

A3. Survey questions (translated)

1. What is your age? (years)
2. What is your gender? By gender we mean gender identity, that is, the gender you identify with.
   -Female
   -Male
   -Other or unsure
3. What is your civil status?
   -Single
   -Married/domestic partnership
4. What is your highest level of education?
   -Lower secondary or similar
   -Upper secondary
   -University or college education
5. Estimate your total monthly income before tax (including salary, pension, social security, sickness benefit).
   -0 – 5,000 kr
   -5,000 – 10,000 kr
   -10,000 – 15,000 kr
   -15,000 – 20,000 kr
   -20,000 – 25,000 kr
   -25,000 – 30,000 kr
   -30,000 – 35,000 kr
   -35,000 – 40,000 kr
   -40,000 – 45,000 kr
   -45,000 – 50,000 kr
   -50,000 – 55,000 kr
   -55,000 – 60,000 kr
   -60,000 kr or higher
   -Prefer not to say
6. Which model year is your car? (If you own more than one car state the age of the newest.)[41]
7. Estimate your car's mileage. (If you own more than one car state the mileage of the newest.)
   -0 – 50,000 km
   -50,000 – 100,000 km
   -100,000 – 150,000 km
   -150,000 – 200,000 km
   -200,000 – 250,000 km
   -250,000 – 300,000 km
   -300,000 – 350,000 km

[41] 22 observations that are less than or equal to 18 are assumed to be age and have been converted into model year by subtracting from 2018. 6 observations appear to have spelling errors and have been corrected accordingly: 82, 89, 98 have been recoded as 1982, 1989 and 1998, while 204 and 215 have been recoded as 2004 and 2015.

-350,000 – 400,000 km
-400,000 km or higher

8. How many times have you inspected your car?
   -Never
   -1-3 times
   -4-6 times
   -7-9 times
   -10 times or more
9. Have you ever had your car fail an inspection with a requirement for re-inspection?
   -No
   -Yes, once
   -Yes, twice or more
10. Do you think that the weekday on which a car is inspected plays a role in the car passing the inspection?
   -No
   -Yes, but not much
   -Yes, a lot
11. (For those that answer yes above) On which weekday do you think that the chance of the car passing inspection is highest?
   -Monday
   -Tuesday
   -Wednesday
   -Thursday
   -Friday
12. Do you think that the weather on inspection day plays a role in a car passing the inspection?
   -No
   -Yes, but not much
   -Yes, a lot
13. (For those that answer yes above) What type of weather do you think that the chance of the car passing inspection is highest?
   -Overcast
   -Mostly cloudy
   -Partly cloudy
   -Mostly sunny
   -Clear
14. If the inspector receives his/her salary on inspection day, do you think that this plays a role in a car passing the inspection?
   -Yes, on payday the chance of the car passing decreases a lot
   -Yes, on payday the chance of the car passing decreases a little
   -No
   -Yes, on payday the chance of the car passing increases a little
   -Yes, on payday the chance of the car passing increases a lot
15. Do you think there are car owners in Sweden who try to increase the chance of their car passing the inspection by taking into account the weekday when they inspect their cars?

-No
-Yes, some
-Yes, many

16. Do you think there are car owners in Sweden who try to increase the chance of their car passing the inspection by taking into account the weather when they inspect their cars?
-No
-Yes, some
-Yes, many
17. Do you think there are car owners in Sweden who try to increase the chance of their car passing the inspection by taking into account payday when they inspect their cars?
-No
-Yes, some
-Yes, many
18. In a typical week, indicate on which weekday you think that most people in Sweden consider themselves to be in the best mood, that is, feel the happiest.
-Monday
-Tuesday
-Wednesday
-Thursday
-Friday
19. Indicate in which type of weather you think that most people in Sweden consider themselves to be in the best mood, that is, feel the happiest.
-Overcast
-Mostly cloudy
-Partly cloudy
-Mostly sunny
-Clear
20. Indicate on a scale between 1 to 5 which mood you feel you are in today.
-1 very depressed
-2 quite depressed
-3 neither depressed nor happy
-4 quite happy
-5 very happy

A4. Failure definition in Swedish dataset

The dataset does not tell us the result of each inspection. We therefore construct this variable in the following way. For each inspection, we define a variable *period* to be the number of days between the inspection date and the expiry date. The inspection result determines when a car is required to return for the next inspection, whether that be a regular inspection the year after or a re-inspection within a month or a week. Inspection results are thus expected to correspond to the period variable. A car that has passed or only has minor defects does not need to return for another inspection for another year, such a car is expected to have a period of 365. A car that has major defects and needs to be re-inspected will have a period of either 30 or 7 (if it has failed three times in a row). A car that has a driving ban imposed cannot be driven at all, it needs to be immediately repaired and re-inspected. In these cases, it is unclear what date inspectors record in the field "expiry date". There are for example 24 cases in which the expiry date is equal to the inspection date, or 3,947 cases with missing expiry date. We therefore make the monotonicity assumption that inspections resulting in a driving ban will not have period exceeding inspections resulting in a call for re-inspection. We subsequently drop the 3,947 observations with missing expiry date and 43 observations with negative period, ending up with 5,819,509 observations.

To complicate matters, period does not have a discrete distribution across values 7, 30 and 365. The distribution of period is displayed in Figure 6. The graph shows spikes close to 0, presumably inspections resulting in re-inspections, and around the one year mark for the next regular inspection of cars that have passed. The bars around 700-800 correspond to cars which have been inspected once and whose second inspection falls two years later, but there are also a number of inspections with even higher periods. We therefore assume that all observations with period greater than or equal to a year to be passes.

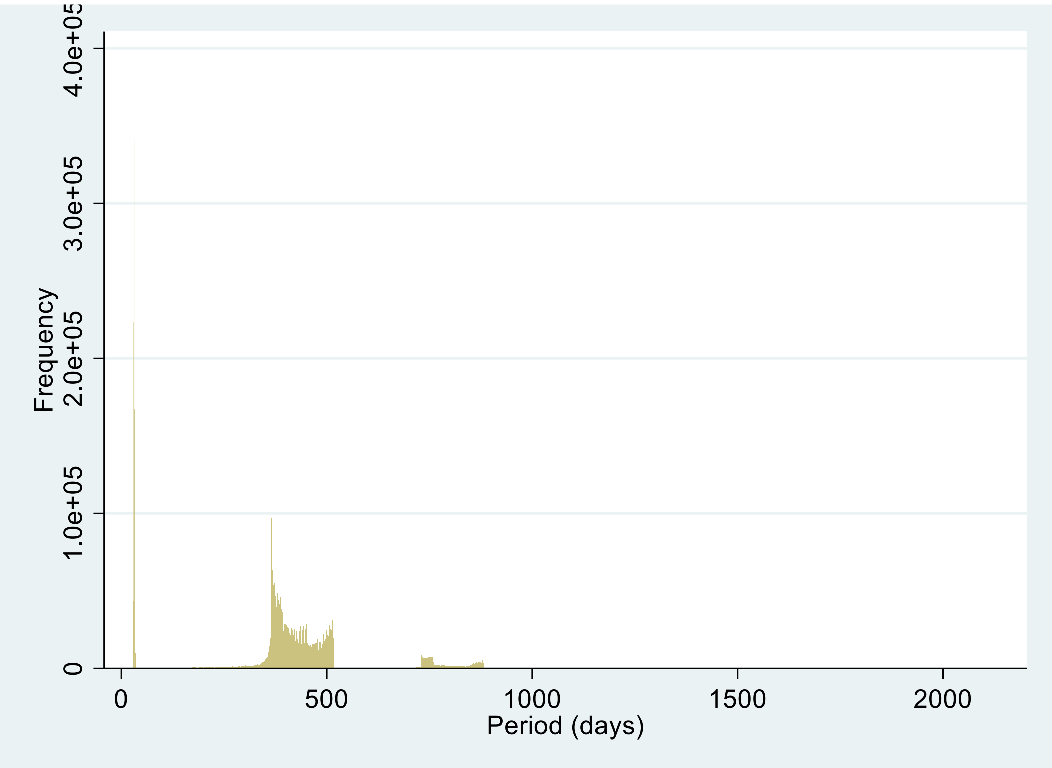

Figure 6 Distribution of period, whole sample

Focusing on inspections with period less than a year, displayed in Figure 7, there is a clear spike around the one month mark for cars that have major defects and are required to return for re-inspection, and similarly at the one week mark for cars that have failed three times in a row. We therefore classify all observations with period less than or equal to 35 to be fails, which also include driving bans.

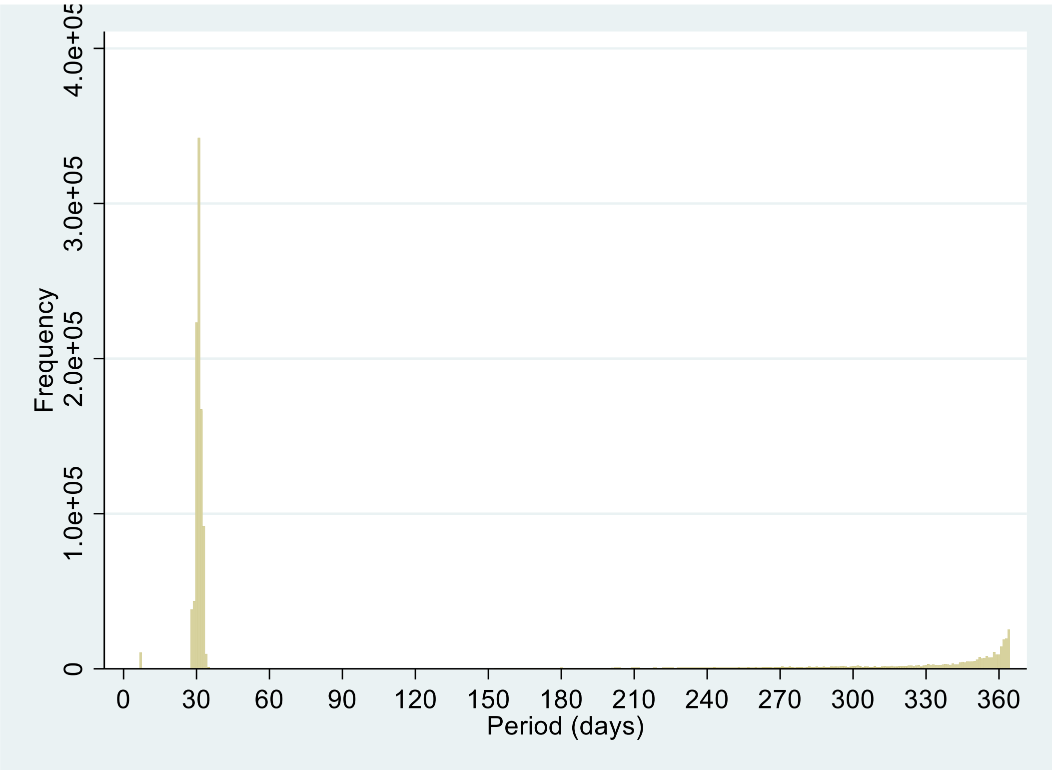

Figure 7 Distribution of period less than a year

There are however inspections with period between a month and a year, shown in Figure 8 below. It is doubtful that inspections with period from about 150 onwards result in fails, given traffic safety concern. A plausible reason for why the period is less than a year is that the car has been delisted and, upon relisting, the inspection is done less than a year before the usual inspection period. We therefore assume that observations with period greater than or equal to 150 days to be passes. A spot-check of a random sample of registration numbers on a third-party website reveals that this is indeed the case.[42]

[42] The website http://biluppgifter.se publishes data including registration details and past inspection results based on the car's registration number.

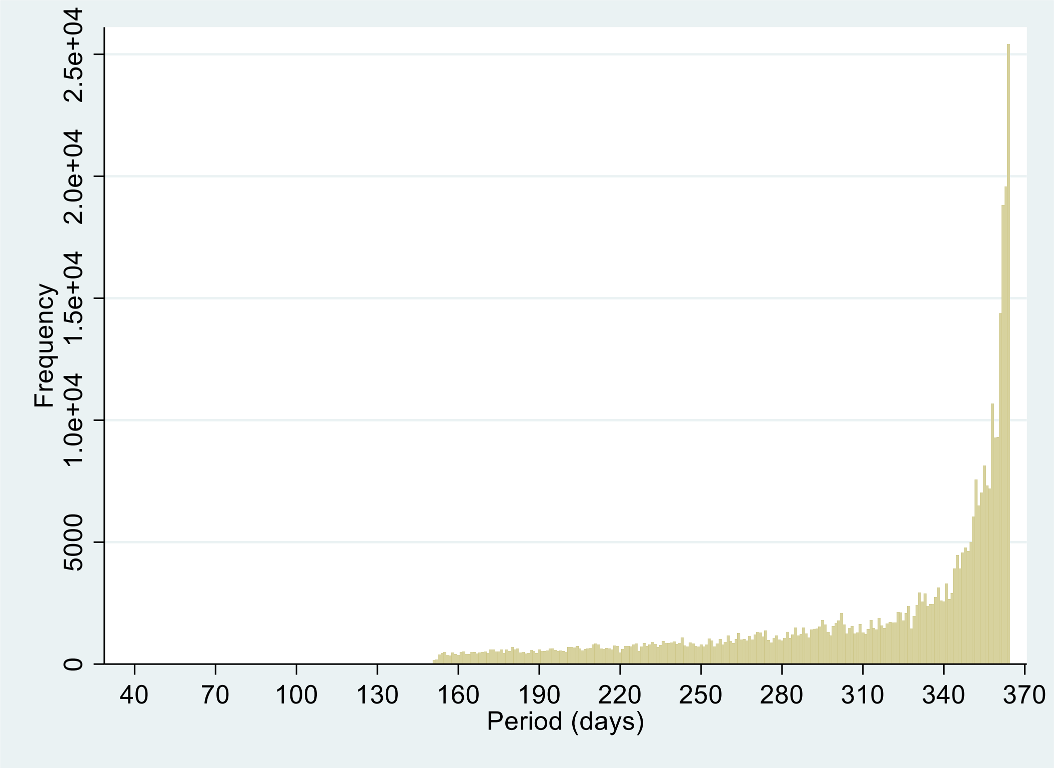

Figure 8 Distribution of period between 35 and 365 days

What remains to be determined is the results of inspections with period between 35 and 150 days. The distribution is shown in Table 14. Random spot-checks on the third-party website of inspections with period up to and including 63 confirm that these are fails. No inspection result was available for the inspection with period of 64.[43] Inspections with 91and 106 days until expiry are passes.

Table 14 Distribution of period between 35 and 150 days

Period	Frequency
36	4
37	15
38	24
39	2
40	1
41	1
46	1
57	2
59	2
60	3
61	16
62	2

[43] On http://biluppgifter.se it is only stated that on the inspection date the car was pre-registered and no inspection result was recorded.

63	1
64	1
91	1
106	1

Based on the above checks we therefore proceed to classify **inspections with period less than 64 days between the inspection date and expiry date as fails and otherwise as passes.** We do not expect our results to be changed by altering this assumption by a few days, given the small number of observations concerned.

A5. Model

We develop a theoretical explanation below that explains car owners' strategic behavior in targeting inspection days. The model aims to explain why we expect low quality cars to be most prevalent for inspections on certain days when inspectors are expected to be in a good mood, i.e. why it is only owners of low quality cars that would exploit the effect of, for example, Friday on passing the inspection.

In a pool of cars of type t, where t signifies quality and is determined by mileage in '000 km (among other things), the proportion of cars with flaws is q and the proportion of cars with no flaws is $1 - q$. For simplicity, let q be a discrete function of the car's mileage $q(k)$, such that $q(1) < q(2) < q(3) < \cdots$. It is assumed that an inspector can only find flaws in a pool of cars with flaws ($q > 0$) but does not always find it, which is reasonable in the car inspection setting. Whether or not a flaw is detected depends on the inspector's judgment, reflected by the probability p that the inspector finds the car faulty and fails it. This probability is assumed to depend positively on the inspector's strictness s which is a subjective attitude and a function of his mood m. Strictness is assumed to decrease with mood, as good mood is often associated with a more simplistic information processing while bad mood tends to stimulate more analytical information processing (Batra & Stayman, 1990; Bless et al., 1990, 1996; Hertel et al., 2000; Sinclair & Mark, 1995). Thus, $s'(m) < 0$. For simplicity assume that the extra cost to the owner of a car that does not pass is fixed and given by C.

If we disregard other costs from not passing (besides C), the expected cost to the car owner of an inspection is given by:

$$E(cost) = p\big(s(m)\big)q(k)C$$

That is, the expected cost is simply the cost of failing C times the probability of failing, which equals the probability that the car has a flaw $q(k)$ times the probability that the flaw is detected $p(s(m))$.

Note that the expected cost of inspecting is decreasing in the inspector's mood since $\frac{dE(cost)}{dm} = \frac{dp}{ds}\frac{ds}{dm}q(k)C < 0$, and by assumption $\frac{dp}{ds} > 0$ and $\frac{ds}{dm} < 0$. By construction these derivatives are not affected by the mileage of the car. Hence, the larger $q(k)$ the more does the expected cost of inspecting the car increase which means that car owners with higher mileage cars have more to gain from an increase in the mood of inspectors, as there are more flawed cars in the pool of higher mileage cars.

A6. Robustness checks

The next two sections present robustness checks for our analysis. For comparison purposes, Table 15 containing the original results is reproduced below.

Table 15 Summary of regression results

	Friday	Good weather	Unexpected win
SWEDEN			
(1) Mood effect on fail	0.00775***	-0.00103	0.00897
(2) Selection effect (Km)	7.92e-05***	-3.12e-05***	-2.15e-07
Obs.	5,806,925	2,695,306	5,806,925
ENGLAND			
(1) Mood effect on fail	-0.0136***	0.00269***	0.00415
(2) Selection effect (Km)	3.00e-05***	-9.34e-06***	-7.67e-09
Obs.	41,402,699	20,844,258	41,402,699

Row (1): Coefficients from OLS regressions of likelihood of failing inspection on mood source as given by column title. Row (2): Coefficients from OLS regressions of likelihood of choosing for inspection the day given by the column title on Km. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Km*: mileage of car in '000 km. All regressions control for km ('000), inspection year (except for "Good weather" column which only includes 2016 data), green fuel, car make, with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

As these robustness checks show, while the quantitative results change slightly, the overall qualitative conclusion is unchanged: mood has an inconsistent effect on failure rates.

A6.1 All mood effects in the same regression

In Table 16 all mood effects (Friday, good weather and unexpected wins) are controlled for in the same regression of failure rates.

Table 16 Regression results for all mood effects

	(1) SWE 2016-2017 Fail	(2) SWE 2016 Fail	(3) ENG 2016 Fail
Friday	0.00789***	0.00514***	-0.0138***
	(0.000526)	(0.000705)	(0.000515)
Good weather	-0.000372	-0.00100	0.00199***
	(0.000492)	(0.000855)	(0.000214)
Unexpected win	0.00996	0.0207*	0.00204
	(0.00809)	(0.00803)	(0.00426)

Kilometer	0.00133***	0.00133***	0.00131***
	(1.84e-05)	(1.90e-05)	(4.12e-05)
Inspection year	-0.000854		
	(0.00102)		
Green	0.00709	0.00932	-0.0699***
	(0.00571)	(0.00773)	(0.00384)
Constant	-0.00964***	-0.00806***	0.227***
	(0.00252)	(0.00268)	(0.00464)
Observations	5,429,289	2,695,306	20,844,258
R-squared	0.101	0.101	0.066

OLS regressions of likelihood of failing inspection. Column (1): all data in Sweden, column (2): 2016 data in Sweden, column (3): 2016 data in England. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.2 Monday

In Table 17 we check for bad mood effect on Mondays.

Table 17 Regression results for Monday

	(1) SWE Fail	(2) SWE Mon	(3) ENG Fail	(4) ENG Mon
Monday	-0.00597***		0.00812***	
	(0.000476)		(0.000412)	
Kilometer	0.00132***	-2.43e-05***	0.00127***	-1.03e-05***
	(1.77e-05)	(2.99e-06)	(4.05e-05)	(2.43e-06)
Inspection year	-0.00125	-0.000617	-0.00566***	-0.00242***
	(0.000972)	(0.000605)	(0.000456)	(0.000145)
Green	0.00707	-0.000351	-0.0732***	0.00417**
	(0.00532)	(0.00599)	(0.00341)	(0.00153)
Constant	-0.00620*	0.195***	0.223***	0.199***
	(0.00243)	(0.000787)	(0.00451)	(0.000444)

Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.001	0.065	0.000

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of likelihood of choosing Monday for inspection in Sweden and England respectively. *Monday:* dummy variable which equals 1 if the car is inspected on a Monday. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.3 All weekdays as dummy variables

In Table 18 we control for all weekdays as dummy variables, using Monday as the base variable.

Table 18 Regression results for all weekdays as dummy variables, using Monday as base variable

	(1) SWE Fail	(2) ENG Fail
Tuesday	0.00396***	-0.00257***
	(0.000545)	(0.000260)
Wednesday	0.00175***	-0.00471***
	(0.000551)	(0.000396)
Thursday	0.00728***	-0.00840***
	(0.000670)	(0.000471)
Friday	0.0110***	-0.0175***
	(0.000609)	(0.000684)
Kilometer	0.00132***	0.00127***
	(1.77e-05)	(4.05e-05)
Inspection year	-0.00125	-0.00564***
	(0.000972)	(0.000456)
Green	0.00698	-0.0733***
	(0.00532)	(0.00341)
Constant	-0.0121***	0.231***
	(0.00239)	(0.00432)
Observations	5,806,925	41,402,699
R-squared	0.100	0.065

Columns (1) and (2): OLS regressions of likelihood of failing inspection in Sweden and England respectively. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.4 All weekdays as a numerical variable

In Table 19 we use weekday as a numerical variable to check if failure is lower and selection is higher later in the week.

Table 19 Regression results for all weekdays as a numerical variable

	(1) SWE Fail	(2) SWE Weekday	(3) ENG Fail	(4) ENG Weekday
Weekday	0.00253***		-0.00408***	
	(0.000145)		(0.000159)	
Kilometer	0.00132***	0.000250***	0.00127***	8.78e-05***
	(1.77e-05)	(1.02e-05)	(4.05e-05)	(1.17e-05)
Inspection year	-0.00127	0.0107***	-0.00564***	0.00859***
	(0.000971)	(0.00226)	(0.000456)	(0.000475)
Green	0.00698	0.0368	-0.0733***	-0.0144
	(0.00532)	(0.0215)	(0.00341)	(0.00736)
Constant	-0.0149***	2.995***	0.236***	2.964***
	(0.00243)	(0.00266)	(0.00423)	(0.00222)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.002	0.065	0.000

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing one day later for inspection in Sweden and England respectively. *Weekday:* variable which equals 1, 2, 3, 4, 5 for inspections done on Monday, Tuesday, Wednesday, Thursday, Friday respectively. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.5 Bad weather

In Table 20 we check for any bad mood effect from bad weather, defined as a day when the cloud cover (Sweden) or rainfall (England) is higher than average for that week and geographic area.

Table 20 Regression results for bad weather

	(1) SWE Fail	(2) SWE Bad weather	(3) ENG Fail	(4) ENG Bad weather
Bad weather	0.00103		-0.00276***	
	(0.000849)		(0.000237)	
Kilometer	0.00133***	3.14e-05***	0.00131***	1.16e-05***
	(1.90e-05)	(5.01e-06)	(4.11e-05)	(1.73e-06)
Green	0.00932	-0.0164	-0.0699***	0.000855
	(0.00773)	(0.00837)	(0.00385)	(0.00195)
Constant	-0.00803***	0.553***	0.226***	0.334***
	(0.00267)	(0.00131)	(0.00463)	(0.000495)
Observations	2,695,306	2,695,306	20,844,258	20,844,258
R-squared	0.101	0.005	0.066	0.002

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively using 2016 data. Columns (2) and (4): OLS regressions of bad weather using 2016 data. *Bad weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is positive. *Kilometer*: mileage of car in '000 km. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.6 Continuous deseasonalised weather

In Table 21 we have used raw deseasonalised weather variables, cloud cover in Sweden and rainfall in England, as mood variables.

Table 21 Regression results for continuous deseasonalised weather

	(1) SWE Fail	(2) SWE Cloud cover	(3) ENG Fail	(4) ENG Rainfall
Weather	0.000779***		-0.000225***	
	(0.000220)		(3.37e-05)	
Kilometer	0.00133***	0.000113***	0.00131***	3.79e-05***
	(1.90e-05)	(2.17e-05)	(4.11e-05)	(1.14e-05)
Green	0.00935	-0.0493	-0.0699***	0.00672
	(0.00773)	(0.0390)	(0.00385)	(0.0134)

Constant	-0.00733**	-0.159***	0.226***	-0.00157
	(0.00265)	(0.00647)	(0.00466)	(0.00328)
Observations	2,695,306	2,695,306	20,844,258	20,844,258
R-squared	0.101	0.003	0.066	0.000

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively using 2016 data. Columns (2) and (4): OLS regressions of inspection day deseasonalised cloud cover in Sweden and rainfall in England respectively using 2016 data. *Weather:* cloud cover in octa for Sweden and rainfall in mm for England, deseasonalised by week and town/postcode area. *Kilometer*: mileage of car in '000 km. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.7 Non-deseasonalised weather

In Table 22 we have used the non-deseasonalised weather variables, cloud cover in Sweden and rainfall in England, as mood variables.

Table 22 Regression results for non-deseasonalised weather

	(1) SWE Fail	(2) SWE Cloud cover	(3) ENG Fail	(4) ENG Rainfall
Weather	0.00132***		-0.000278***	
	(0.000255)		(3.15e-05)	
Kilometer	0.00133***	0.000349***	0.00131***	7.08e-05***
	(1.90e-05)	(2.79e-05)	(4.11e-05)	(2.03e-05)
Green	0.00937	-0.0469	-0.0699***	-0.0357*
	(0.00774)	(0.0423)	(0.00385)	(0.0165)
Constant	-0.0144***	5.256***	0.226***	1.955***
	(0.00289)	(0.00810)	(0.00466)	(0.00394)
Observations	2,695,306	2,695,306	20,844,258	20,844,258
R-squared	0.101	0.027	0.066	0.018

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively using 2016 data. Columns (2) and (4): OLS regressions of inspection day cloud cover in Sweden and rainfall in England respectively using 2016 data. *Weather:* cloud cover in octa for Sweden and rainfall in mm for England. *Kilometer*: mileage of car in '000 km. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.8 Unexpected losses

In Table 23 we have used unexpected loss as a bad mood variable. Unexpected loss is a dummy variable which equals 1 if the inspection day falls after a local soccer team lost despite lower odds of winning, and 0 otherwise.

Table 23 Regression results for unexpected loss days

	(1) SWE Fail	(2) SWE Unexpected loss	(3) ENG Fail	(4) ENG Unexpected loss
Unexpected loss	0.00430		0.00770***	
	(0.00594)		(0.00215)	
Kilometer	0.00132***	-3.09e-07	0.00127***	1.80e-07
	(1.78e-05)	(2.84e-07)	(4.05e-05)	(1.05e-07)
Inspection year	-0.00124	-0.000197	-0.00568***	0.000118
	(0.000973)	(0.000500)	(0.000456)	(0.000149)
Green	0.00708	-4.15e-05	-0.0732***	-1.79e-05
	(0.00532)	(0.000319)	(0.00340)	(2.28e-05)
Constant	- 0.00737***	0.00155***	0.224***	0.000354***
	(0.00242)	(0.000286)	(0.00447)	(7.02e-05)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.010	0.065	0.005

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing unexpected loss days for inspection in Sweden and England respectively. *Unexpected loss:* dummy variable which equals 1 if the car is inspected on a day after the local soccer team lost a match unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.9 Wins

In Table 26 we have used win as a mood variable, a dummy variable which equals 1 if the inspection day falls after a local soccer team won, and 0 otherwise, regardless of odds.

Table 24 Regression results for win days

	(1) SWE Fail	(2) SWE Win	(3) ENG Fail	(4) ENG Win

Win	0.00486		0.00428*	
	(0.00436)		(0.00173)	
Kilometer	0.00132***	-1.19e-06	0.00127***	5.91e-09
	(1.77e-05)	(6.15e-07)	(4.05e-05)	(1.22e-07)
Inspection year	-0.00124	-0.000701	-0.00567***	-0.000698
	(0.000973)	(0.000921)	(0.000456)	(0.000558)
Green	0.00707	0.00136	-0.0732***	-1.39e-05
	(0.00532)	(0.00136)	(0.00340)	(5.00e-05)
Constant	-0.00739***	0.00596***	0.224***	0.00190***
	(0.00241)	(0.000572)	(0.00447)	(0.000273)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.036	0.065	0.016

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing win days for inspection in Sweden and England respectively. *Win:* dummy variable which equals 1 if the car is inspected on a day after the local soccer team won a match. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

A6.10 Losses

In Table 25 we have used loss as a bad mood variable, a dummy variable which equals 1 if the inspection day falls after a local soccer team lost, and 0 otherwise, regardless of odds.

Table 25 Regression results for loss days

	(1) SWE Fail	(2) SWE Loss	(3) ENG Fail	(4) ENG Loss
Loss	0.000230		0.00434**	
	(0.00557)		(0.00158)	
Kilometer	0.00132***	-1.96e-06**	0.00127***	-5.71e-08
	(1.77e-05)	(7.05e-07)	(4.05e-05)	(2.04e-07)
Inspection year	-0.00124	-0.000205	-0.00568***	0.000518
	(0.000973)	(0.00168)	(0.000456)	(0.000618)
Green	0.00708	0.000541	-0.0732***	-0.000207
	(0.00532)	(0.000940)	(0.00340)	(0.000106)

Constant	-0.00736***	0.00598***	0.224***	0.00234***
	(0.00241)	(0.000856)	(0.00447)	(0.000300)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.025	0.065	0.018

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing loss days for inspection in Sweden and England respectively. *Loss:* dummy variable which equals 1 if the car is inspected on a day after the local soccer team lost a match. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.11 Matchday

In Table 26 we have used match day as a mood variable. *Matchday* is a dummy variable which equals 1 if the inspection day falls after a local soccer team match, regardless of result, and 0 otherwise.

Table 26 Regression results for matchday

	(1) SWE Fail	(2) SWE Match	(3) ENG Fail	(4) ENG Match
Matchday	0.00690**		0.00535***	
	(0.00254)		(0.00108)	
Kilometer	0.00132***	-2.57e-06**	0.00127***	2.08e-07
	(1.78e-05)	(9.17e-07)	(4.05e-05)	(3.48e-07)
Inspection year	-0.00124	-0.000113	-0.00568***	0.000386
	(0.000975)	(0.00298)	(0.000456)	(0.000761)
Green	0.00707	0.00132	-0.0732***	-0.000140
	(0.00532)	(0.00124)	(0.00340)	(9.46e-05)
Constant	-0.00747***	0.0151***	0.224***	0.00523***
	(0.00243)	(0.00153)	(0.00447)	(0.000377)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.070	0.065	0.041

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing matchday for inspection in Sweden and England respectively. *Matchday:* dummy variable which equals 1 if the car is inspected on a day after the local soccer team played a match. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.12 All bad mood effects in the same regressions

In Table 27 we have controlled for all bad mood sources in the same regression, again finding inconsistent effects.

Table 27 Regression results for all bad mood effects

	(1) SWE 2016-2017 Fail	(2) SWE 2016 Fail	(3) ENG 2016 Fail
Monday	-0.00591***	-0.00516***	0.00855***
	(0.000480)	(0.000702)	(0.000416)
Bad weather	6.85e-05	0.00107	-0.00240***
	(0.000500)	(0.000852)	(0.000229)
Unexpected loss	0.00627	0.00833	0.00698
	(0.00585)	(0.00797)	(0.00395)
Kilometer	0.00133***	0.00133***	0.00131***
	(1.84e-05)	(1.90e-05)	(4.12e-05)
Inspection year	-0.000814		
	(0.00102)		
Green	0.00717	0.00933	-0.0699***
	(0.00571)	(0.00773)	(0.00384)
Constant	-0.00713***	-0.00706**	0.225***
	(0.00250)	(0.00270)	(0.00467)
Observations	5,429,289	2,695,306	20,844,258
R-squared	0.101	0.101	0.066

OLS regressions of likelihood of failing inspection. Column (1): all data in Sweden, column (2): 2016 data in Sweden, column (3): 2016 data in England. *Monday*: dummy variable which equals 1 if the car is inspected on a Monday. *Bad weather*: dummy variable which equals 1 if cloud cover (Sweden) or rainfall (England), deseasonalised by week and town/postcode area, is positive. *Unexpected loss*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team lost unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.13 Last working day before public holidays

In Table 28 we have used *Lastday*, the last working day before public holidays, as a good mood variable. In Sweden, these consist of all Fridays plus seven additional days. In England these consist of all Friday plus two additional days.

Table 28 Regression results for last working day before public holidays

	(1) SWE Fail	(2) SWE Lastday	(3) ENG Fail	(4) ENG Lastday
Lastday	0.00670***		-0.0140***	
	(0.000492)		(0.000481)	
Kilometer	0.00132***	7.51e-05***	0.00127***	2.71e-05***
	(1.77e-05)	(2.96e-06)	(4.05e-05)	(3.11e-06)
Inspection year	-0.00130	0.00796***	-0.00567***	0.000658***
	(0.000972)	(0.000725)	(0.000456)	(0.000128)
Green	0.00698	0.0138*	-0.0733***	-0.00535*
	(0.00532)	(0.00585)	(0.00341)	(0.00208)
Constant	-0.00878***	0.211***	0.227***	0.193***
	(0.00242)	(0.000793)	(0.00442)	(0.000623)
Observations	5,806,925	5,806,925	41,402,699	41,402,699
R-squared	0.100	0.003	0.065	0.000

Columns (1) and (3): OLS regressions of likelihood of failing inspection in Sweden and England respectively. Columns (2) and (4): OLS regressions of choosing lastday for inspection in Sweden and England respectively. *Lastday:* dummy variable which equals 1 if the car is inspected on a weekday which precedes a public holiday or weekend. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for geographical area (station town for Sweden or postcode area for England) and standard errors clustered at this geographical area level. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

A6.14 Age

In Table 29 and Table 30 we repeat our main analysis controlling for age.

Table 29 Regression results controlling for age in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00653***					
	(0.000505)					
Good weather			-0.00190*			
			(0.000819)			
Unexpected win					0.00689	
					(0.00820)	
Kilometer	0.00113***	6.16e-05***	0.00114***	-4.95e-05***	0.00113***	-5.18e-07
	(1.56e-05)	(2.90e-06)	(1.68e-05)	(5.03e-06)	(1.56e-05)	(3.42e-07)
Age	0.00709***	0.000649***	0.00727***	0.000695***	-0.00188	-0.000340
	(0.000121)	(3.50e-05)	(0.000137)	(6.37e-05)	(0.000974)	(0.000604)
Inspection year	-0.00191	0.00419***			0.00709***	1.12e-05*
	(0.000973)	(0.000739)			(0.000121)	(4.54e-06)
Green	0.0278***	0.0149*	0.0312***	0.0186*	0.0279***	-0.000182
	(0.00541)	(0.00580)	(0.00784)	(0.00836)	(0.00542)	(0.000512)
Constant	-0.0920***	0.188***	-0.0932***	0.438***	-0.0908***	0.00180***
	(0.00340)	(0.000917)	(0.00378)	(0.00137)	(0.00340)	(0.000329)

Observations	5,806,918	5,806,918	2,695,303	2,695,303	5,806,918	5,806,918
R-squared	0.116	0.003	0.117	0.005	0.115	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Age*: age of car in years. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Table 30 Regression results controlling for age in England

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	-0.0126***					
	(0.000443)					
Good weather			0.00243***			
			(0.000233)			
Unexpected win					0.00514	
					(0.00356)	
Kilometer	0.000940***	4.80e-05***	0.000972***	-1.50e-05***	0.000940***	4.43e-08
	(3.26e-05)	(3.89e-06)	(3.31e-05)	(1.85e-06)	(3.25e-05)	(1.31e-07)
Age	0.0121***	-0.000614***	0.0125***	0.000233***	0.0121***	-2.05e-06
	(0.000284)	(4.20e-05)	(0.000304)	(3.31e-05)	(0.000285)	(2.37e-06)
Inspection year	-0.00676***	0.00173***			-0.00678***	-0.000127
	(0.000459)	(0.000131)			(0.000459)	(0.000246)
Green	-0.0150***	-0.00741***	-0.0128***	0.000620	-0.0149***	1.48e-05

	(0.00286)	(0.00196)	(0.00355)	(0.00189)	(0.00286)	(1.59e-05)
Constant	0.146***	0.192***	0.139***	0.658***	0.143***	0.000641***
	(0.00499)	(0.000602)	(0.00536)	(0.000615)	(0.00505)	(0.000114)
Observations	41,246,137	41,246,137	20,761,204	20,761,204	41,246,137	41,246,137
R-squared	0.081	0.000	0.082	0.002	0.080	0.005

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Age*: age of car in years. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.15 Diesel cars

In Table 31 and Table 32 we have used the original mood variables and controlled for diesel fuel type (instead of green fuel type).

Table 31 Regression results controlling for diesel cars in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00788***					
	(0.000507)					
Good weather			-0.00113			
			(0.000835)			
Unexpected win					0.00809	
					(0.00826)	

Kilometer	0.00129***	8.00e-05***	0.00130***	-3.21e-05***	0.00129***	-2.70e-07
	(1.72e-05)	(2.87e-06)	(1.84e-05)	(5.02e-06)	(1.72e-05)	(2.81e-07)
Inspection year	0.00127	0.00419***			0.00131	-0.000335
	(0.000968)	(0.000740)			(0.000969)	(0.000604)
Diesel	-0.0742***	0.00161***	-0.0740***	-0.00195*	-0.0742***	-0.000115*
	(0.00134)	(0.000527)	(0.00143)	(0.000798)	(0.00134)	(4.52e-05)
Constant	0.00720***	0.196***	0.00937***	0.447***	0.00872***	0.00196***
	(0.00225)	(0.000771)	(0.00246)	(0.00134)	(0.00224)	(0.000345)
Observations	5,806,925	5,806,925	2,695,306	2,695,306	5,806,925	5,806,925
R-squared	0.107	0.003	0.107	0.005	0.106	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Diesel*: dummy variable which equals 1 if the car's fuel type is diesel. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

Table 32 Regression results controlling for diesel cars in England

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	-0.0134***					
	(0.000467)					
Good weather			0.00263***			
			(0.000236)			
Unexpected win					0.00425	

					(0.00384)	
Kilometer	0.00136***	2.69e-05***	0.00139***	-8.05e-06***	0.00136***	-1.52e-08
	(4.14e-05)	(2.95e-06)	(4.20e-05)	(1.84e-06)	(4.14e-05)	(1.07e-07)
Inspection year	-0.00491***	0.00162***			-0.00493***	-0.000127
	(0.000458)	(0.000130)			(0.000458)	(0.000246)
Diesel	-0.0603***	0.00246***	-0.0624***	-0.000966***	-0.0603***	5.20e-06
	(0.00123)	(0.000278)	(0.00131)	(0.000226)	(0.00123)	(1.25e-05)
Constant	0.238***	0.187***	0.235***	0.660***	0.236***	0.000626***
	(0.00430)	(0.000631)	(0.00454)	(0.000504)	(0.00434)	(0.000120)
Observations	41,402,699	41,402,699	20,844,258	20,844,258	41,402,699	41,402,699
R-squared	0.069	0.000	0.070	0.002	0.068	0.005

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Diesel*: dummy variable which equals 1 if the car's fuel type is diesel. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.16 Luxury cars

In Table 33 and Table 34 we have controlled for whether or not the car is classified as a luxury car (Gino & Pierce, 2010), which is the case if the car make is any of the following and the car is younger than 10 years: Acura, Rolls Royce, Alfa Romeo, Aston Martin, Audi, Bentley, BMW, Cadillac, Infiniti, Jaguar, Lexus, Lotus, Lamborghini, Maserati, Porsche, Saab, Volvo, Ferrari, and Mercedes-Benz.

Table 33 Regression results controlling for luxury cars in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)

	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00784***					
	(0.000500)					
Good weather			-0.00115			
			(0.000835)			
Unexpected win					0.00848	
					(0.00807)	
Kilometer	0.00121***	8.18e-05***	0.00121***	-3.60e-05***	0.00121***	-3.60e-07
	(1.71e-05)	(2.99e-06)	(1.81e-05)	(5.10e-06)	(1.71e-05)	(2.91e-07)
Inspection year	-0.00185	0.00426***			-0.00181	-0.000340
	(0.000975)	(0.000740)			(0.000977)	(0.000605)
Green	0.00405	0.0131*	0.00572	0.0164	0.00416	-0.000219
	(0.00531)	(0.00581)	(0.00778)	(0.00837)	(0.00531)	(0.000513)
Luxury	-0.0852***	0.00199***	-0.0897***	-0.00369***	-0.0852***	-0.000112
	(0.00176)	(0.000637)	(0.00194)	(0.00118)	(0.00176)	(7.03e-05)
Constant	0.00911***	0.196***	0.0118***	0.447***	0.0106***	0.00196***
	(0.00235)	(0.000791)	(0.00256)	(0.00136)	(0.00235)	(0.000352)
Observations	5,806,925	5,806,925	2,695,306	2,695,306	5,806,925	5,806,925
R-squared	0.104	0.003	0.106	0.005	0.104	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in ‘000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car’s main fuel type is classified as green. *Luxury:* dummy variable which equals 1 if the car is classified to be luxury. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Table 34 Regression results controlling for luxury cars in England

	(1) Fail	(2) Fri	(3) Fail	(4) Good weather	(5) Fail	(6) Unexpected win
Friday	-0.0135***					
	(0.000470)					
Good weather			0.00266***			
			(0.000238)			
Unexpected win					0.00425	
					(0.00401)	
Kilometer	0.00123***	3.44e-05***	0.00127***	-1.03e-05***	0.00123***	1.43e-09
	(3.98e-05)	(3.20e-06)	(4.03e-05)	(1.77e-06)	(3.98e-05)	(1.15e-07)
Inspection year	-0.00583***	0.00168***			-0.00585***	-0.000127
	(0.000455)	(0.000130)			(0.000455)	(0.000246)
Green	-0.0616***	-0.00577***	-0.0563***	-0.000227	-0.0615***	2.26e-05
	(0.00326)	(0.00194)	(0.00322)	(0.00190)	(0.00325)	(1.52e-05)
Luxury	-0.0757***	0.00812***	-0.0812***	-0.00183***	-0.0758***	1.69e-05
	(0.00217)	(0.000485)	(0.00253)	(0.000509)	(0.00217)	(1.50e-05)
Constant	0.232***	0.187***	0.229***	0.660***	0.229***	0.000626***
	(0.00432)	(0.000619)	(0.00457)	(0.000511)	(0.00436)	(0.000119)
Observations	41,402,699	41,402,699	20,844,258	20,844,258	41,402,699	41,402,699

R-squared	0.066	0.000	0.067	0.002	0.066	0.005

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Luxury:* dummy variable which equals 1 if the car is classified to be luxury. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.17 Dropping good quality cars from regression

In Table 35 and Table 36 we show regression results when all cars with less than 100,000 km in mileage are dropped. Since low quality cars are the ones whose inspections involve more discretion, mood effect should be stronger within this group. We do not find that to be the case.

Table 35 Regression results for low quality cars in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00825***					
	(0.000631)					
Good weather			-0.00131			
			(0.00102)			
Unexpected win					0.0100	
					(0.0111)	
Kilometer	0.00139***	7.77e-05***	0.00140***	-9.68e-06	0.00139***	-1.54e-07
	(1.93e-05)	(3.60e-06)	(2.09e-05)	(5.76e-06)	(1.93e-05)	(2.98e-07)
Inspection year	-0.00139	0.00470***			-0.00134	-0.000350
	(0.00118)	(0.000777)			(0.00118)	(0.000612)

Green	0.000819	0.0127	-0.00231	0.00502	0.000926	-0.000266
	(0.00822)	(0.00787)	(0.0112)	(0.0112)	(0.00822)	(0.000502)
Constant	-0.0325***	0.190***	-0.0313***	0.435***	-0.0309***	0.00186***
	(0.00359)	(0.00123)	(0.00379)	(0.00166)	(0.00360)	(0.000329)
Observations	4,096,439	4,096,439	1,914,282	1,914,282	4,096,439	4,096,439
R-squared	0.075	0.003	0.076	0.005	0.075	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in ‘000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Table 36 Regression results for low quality cars in England

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	-0.0198***					
	(0.000661)					
Good weather			0.00399***			
			(0.000337)			
Unexpected win					0.00728	
					(0.00497)	
Kilometer	0.000612***	-6.73e-06	0.000639***	-2.69e-06	0.000612***	-5.10e-09
	(3.04e-05)	(3.50e-06)	(3.12e-05)	(1.93e-06)	(3.03e-05)	(1.63e-07)
Inspection year	-0.00518***	0.00113***			-0.00520***	-0.000105

	(0.000615)	(0.000174)			(0.000615)	(0.000253)
Green	-0.103***	-0.0124***	-0.0992***	-0.00153	-0.103***	5.56e-05
	(0.00473)	(0.00243)	(0.00625)	(0.00323)	(0.00473)	(5.22e-05)
Constant	0.359***	0.195***	0.355***	0.658***	0.355***	0.000582***
	(0.00498)	(0.000827)	(0.00528)	(0.000663)	(0.00502)	(0.000141)
Observations	22,923,959	22,923,959	11,645,320	11,645,320	22,923,959	22,923,959
R-squared	0.034	0.000	0.033	0.002	0.034	0.006

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.18 Previously failed cars

In Table 37 and Table 38 we control for failure at the previous inspection. According to our survey, owners who have failed more times are the ones more likely to admit belief in the mood effect and should be more likely to select into good mood inspection days.

Table 37 Regression results controlling for previous failure in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00157*					
	(0.000772)					
Good weather			-0.00150			

			(0.00246)			
Unexpected win					-0.00644	
					(0.00725)	
Kilometer	0.00140***	8.00e-05***	0.00112***	-3.05e-05	0.00141***	-3.59e-07
	(1.89e-05)	(4.26e-06)	(2.22e-05)	(1.80e-05)	(1.89e-05)	(4.57e-07)
Inspection year	-0.0186***	-0.00412***			-0.0186***	0.000246
	(0.00240)	(0.00133)			(0.00240)	(0.000583)
Green	0.0187	0.0295***	0.0568	0.0202	0.0184	0.000566
	(0.0107)	(0.00924)	(0.0442)	(0.0423)	(0.0107)	(0.000933)
Previous failure	0.168***	0.00914***	0.249***	0.0146***	0.168***	-0.000114*
	(0.00178)	(0.000856)	(0.00416)	(0.00406)	(0.00177)	(5.21e-05)
Constant	0.0352***	0.198***	0.0590***	0.429***	0.0354***	0.00151**
	(0.00331)	(0.00183)	(0.00636)	(0.00536)	(0.00332)	(0.000571)
Observations	2,409,479	2,409,479	122,830	122,830	2,409,496	2,409,496
R-squared	0.122	0.003	0.160	0.008	0.122	0.012

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Previous failure:* dummy variable which equals 1 if the car failed its last control inspection. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Table 38 Regression results controlling for previous failure in England

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win

Friday	-0.0142***					
	(0.000540)					
Good weather			0.00427***			
			(0.000922)			
Unexpected win					0.00516	
					(0.00681)	
Kilometer	0.000988***	3.03e-05***	0.000631***	-1.40e-05	0.000987***	1.82e-07
	(3.41e-05)	(3.89e-06)	(3.42e-05)	(7.22e-06)	(3.40e-05)	(2.27e-07)
Inspection year	0.0990***	-0.00378***			0.0991***	-7.05e-05
	(0.00259)	(0.00102)			(0.00260)	(0.000267)
Green	-0.0561***	-0.0104***	-0.0270***	-0.00676	-0.0560***	5.54e-05
	(0.00420)	(0.00215)	(0.00530)	(0.00804)	(0.00420)	(7.96e-05)
Previous failure	0.139***	0.00201***	0.0622***	-0.00325	0.139***	-4.76e-06
	(0.00146)	(0.000355)	(0.00291)	(0.00164)	(0.00146)	(9.20e-06)
Constant	0.110***	0.189***	0.151***	0.665***	0.107***	0.000540*
	(0.00576)	(0.000928)	(0.00433)	(0.00280)	(0.00583)	(0.000259)
Observations	16,111,042	16,111,042	804,972	804,972	16,111,045	16,111,045
R-squared	0.076	0.000	0.043	0.003	0.076	0.009

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Previous failure:* dummy variable which equals 1 if the car failed its last control inspection. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A6.19 Logistic regression

In Table 39 and Table 40 we present results using logistic regression instead of the linear probability model. Our results are qualitatively unchanged.

Table 39 Logistic regression results for Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00759***					
	(0.000486)					
Good weather			-0.00118			
			(0.000858)			
Unexpected win					0.00893	
					(0.00772)	
Kilometer	0.00115***	7.82e-05***	0.00116***	-3.13e-05***	0.00115***	-1.22e-06
	(1.14e-05)	(2.82e-06)	(1.18e-05)	(5.03e-06)	(1.14e-05)	(1.61e-06)
Inspection year	-0.00136	0.00425***			-0.00132	-0.00190
	(0.000973)	(0.000744)			(0.000974)	(0.00347)
Green	0.00632	0.0128*	0.00894	0.0164*	0.00641	-0.00127
	(0.00600)	(0.00562)	(0.00868)	(0.00829)	(0.00600)	(0.00331)
Observations	5,806,925	5,794,986	2,695,306	2,695,306	5,806,925	1,030,310

Odd columns: Marginal effects from logistic regressions of likelihood of failing inspection. Even columns: Marginal effects from logistic regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in

‘000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car’s main fuel type is classified as green. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Table 40 Logistic regression results for England

	(1) Fail	(2) Fri	(3) Fail	(4) Good weather	(5) Fail	(6) Unexpected win
Friday	-0.0137***					
	(0.000379)					
Good weather			0.00268***			
			(0.000228)			
Unexpected win					0.00394	
					(0.00382)	
Kilometer	0.00123***	2.98e-05***	0.00127***	-9.34e-06***	0.00123***	-1.18e-07
	(2.97e-05)	(3.08e-06)	(3.05e-05)	(1.80e-06)	(2.97e-05)	(1.07e-06)
Inspection year	-0.00581***	0.00166***			-0.00582***	-0.00112
	(0.000457)	(0.000130)			(0.000456)	(0.00237)
Green	-0.127***	-0.00468*	-0.123***	-0.000528	-0.127***	0.000298*
	(0.00593)	(0.00211)	(0.00641)	(0.00189)	(0.00592)	(0.000134)
Observations	41,402,699	41,402,699	20,844,258	20,844,258	41,402,699	4,710,742

Odd columns: Marginal effects from logistic regressions of likelihood of failing inspection. Even columns: Marginal effects from logistic regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised rainfall is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in ‘000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car’s main fuel type is classified as green. All regressions control for car make with fixed-effects for postcode area and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A7. Robustness checks for Swedish data only

The robustness checks in this section concern the Swedish data only, since they use information not available from the English data (inspection station, inspection due date based on the last digit of the car registration number), and because of missing data issue that only concerns the Swedish data.

A7.1 Station fixed-effects

While the original results for Sweden use town fixed-effects and cluster standard errors at the town level, in Table 41 we use station fixed-effects instead, while still clustering standard errors at the town level.

Table 41 Regression results with station fixed-effects in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00759***					
	(0.000497)					
Good weather			-0.00108			
			(0.000833)			
Unexpected win					0.00906	
					(0.00814)	
Kilometer	0.00132***	7.59e-05***	0.00133***	-3.09e-05***	0.00132***	-2.10e-07
	(1.78e-05)	(2.84e-06)	(1.89e-05)	(4.76e-06)	(1.78e-05)	(2.64e-07)
Inspection year	-0.000941	0.00353***			-0.000911	-0.000395
	(0.000973)	(0.000737)			(0.000974)	(0.000630)
Green	0.00667	0.0125*	0.00910	0.0168*	0.00676	-0.000211
	(0.00527)	(0.00580)	(0.00759)	(0.00832)	(0.00527)	(0.000512)
Constant	-0.00866***	0.197***	-0.00648*	0.447***	-0.00719***	0.00196***

	(0.00242)	(0.000769)	(0.00263)	(0.00130)	(0.00242)	(0.000355)
Observations	5,806,923	5,806,923	2,695,299	2,695,299	5,806,923	5,806,923
R-squared	0.101	0.003	0.103	0.005	0.101	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for inspection station and standard errors clustered at the station town level. *** p<0.005, ** p<0.01, * p<0.05.

A7.2 Controlling for number of inspections per station per year

In Table 42 we control for the average number of inspections done by each station per year, *Num_insp*.

Table 42 Regression results controlling for number of inspections per station per year in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00770***					
	(0.000505)					
Good weather			-0.00102			
			(0.000848)			
Unexpected win					0.00910	
					(0.00816)	
Kilometer	0.00132***	7.73e-05***	0.00133***	-3.07e-05***	0.00132***	-1.72e-07
	(1.76e-05)	(2.89e-06)	(1.87e-05)	(4.88e-06)	(1.76e-05)	(2.82e-07)

Inspection year	-0.00166	0.00378***			-0.00163	-0.000329
	(0.00100)	(0.000699)			(0.00100)	(0.000602)
Green	0.00667	0.0126*	0.00888	0.0166*	0.00677	-0.000207
	(0.00534)	(0.00579)	(0.00774)	(0.00836)	(0.00535)	(0.000514)
Num_insp	-6.35e-07**	-7.61e-07***	-8.01e-07***	1.73e-07	-6.41e-07**	1.67e-08
	(2.36e-07)	(2.13e-07)	(2.75e-07)	(1.40e-07)	(2.36e-07)	(1.30e-08)
Constant	-0.00233	0.204***	0.00121	0.445***	-0.000773	0.00176***
	(0.00302)	(0.00217)	(0.00337)	(0.00179)	(0.00301)	(0.000326)
Observations	5,806,925	5,806,925	2,695,306	2,695,306	5,806,925	5,806,925
R-squared	0.100	0.003	0.101	0.005	0.100	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Num_insp:* average yearly number of inspections done at the inspection station. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

A7.3 Procrastination

In Table 43 we control for car owners' procrastination, that is, if they wait until the last possible date for inspection based on the last digit of their car's registration number. The variable *Procrastination* is defined to be 7 for inspection done on the last possible date, 6 for inspection done a day early, 5 for 2 days early, and so on. *Procrastination* equals 0 for all inspections done at the latest a week before it is due.

Table 43 Regression results controlling for procrastination in Sweden

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win

Friday	0.00491***					
	(0.000480)					
Good weather			-0.00398***			
			(0.000602)			
Unexpected win					0.0104*	
					(0.00511)	
Kilometer	0.00121***	6.43e-05***	0.00122***	-5.43e-05***	0.00122***	-1.37e-07
	(1.61e-05)	(2.80e-06)	(1.75e-05)	(3.98e-06)	(1.61e-05)	(2.11e-07)
Inspection year	-0.00220*	0.00411***			-0.00218*	-0.000338
	(0.000943)	(0.000733)			(0.000943)	(0.000606)
Green	0.00444	0.0126*	0.00636	0.0159	0.00450	-0.000213
	(0.00513)	(0.00579)	(0.00773)	(0.00840)	(0.00513)	(0.000511)
Procrastination	0.0334***	0.00468***	0.0341***	0.00740***	0.0335***	-2.45e-05
	(0.000358)	(0.000141)	(0.000413)	(0.00115)	(0.000358)	(9.40e-05)
Constant	-0.0127***	0.195***	-0.0104***	0.446***	-0.0117***	0.00194***
	(0.00229)	(0.000777)	(0.00250)	(0.00137)	(0.00229)	(0.000338)
Observations	5,806,925	5,806,925	2,695,306	2,695,306	5,806,925	5,806,925
R-squared	0.124	0.003	0.125	0.006	0.124	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. *Procrastination:* variable defined to be 7 for inspection done on the last possible date, 6 for inspection done a day early, 5 for 2 days early, and so on, this variable equals 0 for all inspections done at the latest a week before it is due. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** $p<0.005$, ** $p<0.01$, * $p<0.05$.

A7.4 Missing data

Our original dataset has fewer regular inspections and lower failure rate compared to the figures cited by the Swedish Transport Agency in Table 44. We attempt to identify missing observations using the following method. The raw data includes all types of inspections, including re-inspections. For each re-inspection, we check whether the date listed under variable "last inspection date" matches the actual previous inspection that we have in the dataset for that vehicle registration number. If it does not, then it indicates a missing inspection which we then append to the raw dataset. The variable "last inspection date" is then coded as the missing inspection's "inspection date", the "mileage at last inspection" is coded as the "mileage" at the time of the missing inspection, and the re-inspection's "inspection date" is coded as the missing inspection's "expiry date". We make the assumption that these missing observations are regular inspections, since they immediately precede a re-inspection.[44] Including these missing observations brings our data summary statistics closer to those from the Swedish Transport Agency as shown in Table 44.

Table 44 Comparison of summary statistics with Swedish Transport Agency data

	Raw dataset		Swedish Transport Agency		Raw dataset including missing inspections	
	Total number	Failure rate	Total number	Failure rate	Total number	Failure rate
2016						
Regular inspections	3,163,019	15.93%	3,688,270	26.14%	**3,339,971**	**20.38%**
Re-inspections	972,471	4.48%	820,331	9.05%	972,471	4.48%
2017						
Regular inspections	3,209,166	15.72%	3,738,058	25.83%	**3,695,960**	**26.82%**
Re-inspections	968,299	4.55%	825,629	9.18%	968,299	4.55%

As shown above, we are able to identify a lot more missing observations in 2017. It appears that in 2016 the majority of re-inspections are immediately preceded by an inspection that already exists in our dataset, yielding fewer additional missing inspections. It is unclear why this is the

[44] While a re-inspection can also be immediately preceded by another (failed) re-inspection, the failure rate at re-inspection is much lower (9%) than a regular inspection (26%) according to communication with the Swedish Transport Agency. Additionally, our data discrepancy indicates missing regular inspections rather than re-inspections.

case in 2016 but not 2017. However, as noted in the main text we suspect that these are inspections on older cars owned by business-owners which are often shown as a separate category, which we exclude in the analysis anyway.

Nevertheless, we proceed by cleaning the data and conducting the analysis as in the main text, yielding the results in Table 45.

Table 45 Regression results including missing data identified in original dataset

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00464***					
	(0.000529)					
Good weather			-0.00135			
			(0.000785)			
Unexpected win					0.00851	
					(0.00525)	
Kilometer	0.00159***	7.27e-05***	0.00151***	-3.19e-05***	0.00159***	-2.45e-07
	(2.06e-05)	(2.74e-06)	(2.10e-05)	(5.09e-06)	(2.06e-05)	(2.55e-07)
Inspection year	0.0417***	0.00278***			0.0417***	-0.000340
	(0.00119)	(0.000735)			(0.00120)	(0.000607)
Green	0.00723	0.0172***	0.0123	0.0147	0.00823	2.81e-05
	(0.00561)	(0.00523)	(0.00850)	(0.00853)	(0.00565)	(0.000587)
Constant	-0.0143***	0.197***	0.00281	0.446***	-0.0134***	0.00194***
	(0.00291)	(0.000759)	(0.00300)	(0.00128)	(0.00293)	(0.000356)
Observations	6,263,166	6,263,166	2,820,625	2,820,625	6,262,842	6,262,842
R-squared	0.117	0.002	0.112	0.005	0.117	0.010

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

Communication with the Swedish Transport Agency subsequently confirmed that our original dataset indeed contains only the last inspection for each car in each month. Suppose a car fails a regular inspection early in the month and returns for re-inspection later in the month. Our original dataset thus contains only the second (re-)inspection and misses the first failed (regular) inspection, thus explaining the lower failure rate compared to the Swedish Transport Agency figures. While we have no reason to believe that the effects of our mood sources should differ for these missing inspections occurring early in the month, in the rest of this section we attempt to address this issue.

To complement our earlier robustness check of the missing data we obtained a new dataset from the Swedish Transport Agency which contains all inspections for each vehicle in each month. The new dataset only starts in June 2017, so we are only able to do the analysis for the period June-December 2017. This new dataset contains 12% of observations which are inspections for the same vehicle conducted in the same month on different dates (the corresponding number in the original dataset is 0.22%). Of these repeated observations, around 49% are regular inspections. As expected, the vast majority of these inspections (98%) result in failure. Almost all (99.97%) of these 216,692 failed inspections are missing in our original dataset. Including these missing observations increases the failure rate in the original dataset from 16% to 23%.

We next proceed to analyse whether our results for mood effects are still robust. The new dataset only contains the vehicle registration number, inspection type, inspection date, expiry date, mileage, and inspection station. We therefore match the data with vehicle characteristics (vehicle type, age, fuel type and make) from our original dataset to allow us to control for these variables in the regressions. As in the main analysis, we focus only on regular inspections of cars (vehicle type *personbil*) conducted on weekdays.[45] We end up with 1,967,121 observations.

As seen in Table 46 below, the results are qualitatively the same as our original results.

[45] The new dataset contains around 15% duplicates, where the same car is inspected on the same date but appears twice with different expiry dates. Almost all of these expiry dates are sufficiently far away that the inspection outcome (pass or fail) is not affected. Comparing these duplicates with our original dataset and random checks done on the website https://biluppgifter.se show that the most recent expiry date is the correct one. We therefore drop duplicate observations with the earlier expiry dates. This leaves 0.05% of observations with duplicates whose inspection outcomes do differ. We drop these observations from the analysis.

Table 46 Regression results including missing data from Swedish Transport Agency

	(1)	(2)	(3)	(4)	(5)	(6)
	Fail	Fri	Fail	Good weather	Fail	Unexpected win
Friday	0.00358***					
	(0.000835)					
Good weather			0.00130			
			(0.000753)			
Unexpected win					-0.00881	
					(0.00776)	
Kilometer	0.00155***	8.39e-05***	0.00156***	-3.46e-05***	0.00170***	-2.75e-05
	(2.09e-05)	(4.67e-06)	(2.18e-05)	(5.32e-06)	(0.000111)	(3.49e-05)
Inspection year	-0.0235*	-0.00228	-0.0182	-0.00322	-0.0474	0.0463
	(0.0101)	(0.00689)	(0.0108)	(0.00943)	(0.0437)	(0.0462)
Constant	0.0456***	0.202***	0.0455***	0.446***	0.0321	0.132***
	(0.00296)	(0.00113)	(0.00313)	(0.00142)	(0.0190)	(0.0145)
Observations	1,967,120	1,967,120	1,836,797	1,836,797	26,831	26,831
R-squared	0.104	0.003	0.105	0.003	0.115	0.105

Odd columns: OLS regressions of likelihood of failing inspection. Even columns: OLS regressions of likelihood of choosing that mood day for inspection. *Friday*: dummy variable which equals 1 if the car is inspected on a Friday. *Good weather*: dummy variable which equals 1 if deseasonalised cloud cover is negative. *Unexpected win*: dummy variable which equals 1 if the car is inspected on a day after the local soccer team won unexpectedly. *Kilometer*: mileage of car in '000 km. *Inspection year:* dummy variable which equals 1 if the inspection is conducted in 2017. *Green*: dummy variable which equals 1 if the car's main fuel type is classified as green. All regressions control for car make with fixed-effects for station town and standard errors clustered at this geographical area level. *** p<0.005, ** p<0.01, * p<0.05.

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