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Exploring Psychology in the Field: Steps and Examples From the Used-Car Market

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Abstract

The growing availability of large datasets in a variety of domains presents an opportunity for researchers to use field data to better understand psychological concepts. I discuss, from an empirical economics point of view, steps for how to study cognition in large datasets. I use two recent papers that explore psychology in the used-car market as motivating examples. These examples help illustrate the potential importance of big data as a way to explore human psychology and cognition.

Keywords: Field data; Used-car market

1. Introduction

For many decades, empirical economists have relied primarily on field data as a way to test predictions from theoretical models. With the growth and availability of field data, economics has become an even more empirical discipline and has developed techniques and procedures to work with naturally occurring datasets in order to test hypotheses. Is field data primarily suited for the types of questions that economists ask, or is it possible to study cognition and psychology using field data as well?

The types of research questions asked by economists and psychologists clearly differ to some degree. Like psychologists, economists are interested in how individuals think, behave, and interact. However, where psychologists are often interested in

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understanding the deep underpinnings of behavior at the level of the individual, the primary interest in economics is usually in understanding how individual behavior plays out in a system to shape broader economic outcomes. Naturally occurring field data generated by these economic systems are obviously useful to economists who care about these markets directly. However, in this paper (and as is evident by this special issue), I argue that data from market transactions can be a useful way to explore and better understand psychological concepts as well.[1] Of course, I am not alone in arguing that naturally occurring data can be useful for psychology. Observational data has a rich history in psychology and has been used increasingly over the last decade. One should not be surprised to open a leading psychology journal and find an article with at least one study using observational data. My hope in this article is to provide some basic steps for how to exploit large datasets and to better understand the potential value that these datasets hold.

As motivating examples, I discuss two recent papers (Busse, Pope, Pope, & Silva-Risso, 2015; Lacetera, Pope, & Sydnor, 2012) that explore individual psychology in an important field setting: the used-car market. The first paper tests for evidence of "left-digit bias" in how consumers process the odometer value of a used car. Using data that are available for millions of car transactions, it is shown that cars depreciate discontinuously as the odometer crosses over salient thresholds for which the left-digit changes (e.g., 10,000-mile marks). The second paper tests whether incidental environmental factors such as the weather on the day of purchase can have an impact on the decisions made by car buyers. Specifically, the decision to purchase a convertible or a four-wheel drive vehicle is highly influenced by the weather at the time of purchase. The psychological mechanism that is most consistent with this finding is projection bias. However, the role of other potential biases is also discussed. These two papers show very directly that psychology plays an important role in the used-car market and that this setting can be used to hone our understanding of the psychological concepts involved. I also use these two examples as motivation to discuss specific steps that I argue are important to consider when exploiting large datasets to study psychology.

An important question is the extent to which studies using observational data are simply applying psychology to real-world phenomena or if theoretical contributions to psychology can be made as well. Obviously, field studies can be a useful way to understand which psychological concepts (that have already been discovered) are robust and are important enough to emerge in a real-world market. As of now, the vast majority of studies in behavioral economics that use real-world data are simply applying psychology as opposed to developing new psychology. However, I argue that theoretical contributions using naturally occurring datasets are possible—especially when field data studies are paired with carefully controlled laboratory experiments. I provide a deeper discussion of this issue toward the end of this paper.

This paper proceeds as follows. In Section 2, I provide a general overview of the findings for the two papers that are used as motivation. In Section 3, I provide specific steps for how a researcher may want to proceed when using large datasets to look for important psychology in large field datasets. Once again, I use the two motivating papers as guides to illustrate how each of these steps is done. I conclude in Section 4 with a discussion of when field data may be particularly useful in the study of psychology and when it is likely to not be as effective.

2. Two motivating examples

The first example of exploring psychology using a large field dataset is Lacetera et al. (2012). In this paper, we were interested in exploring how individuals process numbers when making economic decisions. In particular, we focus on the used-car market and the way in which the odometer value for a car influences how consumers assess the vehicle's worth. Our specific hypothesis was that individuals were unlikely to process odometer values in a continuous fashion, but rather would be disproportionately influenced by the left-most digits of numbers while failing to appropriately incorporate digits further to the right (a bias occasionally referred to as left-digit bias). The motivating psychology for this effect is inattention, where consumers simply do not fully process the odometer value for every car they look at. This psychology would lead a car with just under 70,000 miles to be valued much more highly than a car with just over 70,000 miles.[2]

To explore this question, we gained access to data for more than 22 million car transactions that took place in the wholesale market between 2002 and 2008. The wholesale car market is a large market where suppliers of used cars (rental and lease companies, used-car dealers who accept trade-ins, etc.) auction off their cars to other used-car dealers who will then sell the cars on their used-car lots. These data allowed us to easily test whether cars depreciate continuously with miles or if discontinuities in value exist at salient thresholds such as 10,000-mile marks.

As shown further below, we found strong evidence of left-digit bias in the data. Cars just to the right of a 10,000-mile threshold sold for approximately $200 less than cars just to the left of these thresholds. Smaller discontinuities ($15–$20) were found at 1,000-mile marks (e.g., cars just to the right of 28,000 miles sold for less than cars just to the left of the 28,000-mile mark). We interpreted these data as evidence that individuals do not process numbers in a continuous fashion, even when making reasonably large-stake decisions such as purchasing a car.

The second example of exploring psychology using a large field dataset is Busse et al. (2015). Motivated by work on projection bias (Loewenstein, O'Donoghue, & Rabin, 2003) and visceral states (Loewenstein, 1996; Loewenstein & Schkade, 1999), we were interested in understanding how the weather might influence the type of car purchase an individual consumer makes. Our specific hypothesis was that warm, sunny weather would lead to an increase in the number of convertibles purchased and that recent snow would lead to an increase in the number of four-wheel drives purchased.

To investigate this question, we obtained access to a dataset for more than 40 million retail used-car sales around the United States. Controlling for the time of year, we found that higher temperatures and clearer skies led to an increase in the fraction of cars purchased that were convertibles and that recent snow storms led to a large increase in the fraction of cars sold that were four-wheel drives. We argued that these data provided evidence that the consumer's state at the time of purchase is an important factor in the decision of what type of car to buy in a way that is contrary to a standard model of economic behavior.

3. Steps for using field data to study psychology

There are many things to think about when analyzing field data in search for psychological insight. And, of course, not all of these things can be synthesized into a few easy steps. However, below I list a few steps that are likely to generalize across research projects when using large datasets to explore psychology.

3.1. Getting the data

Obviously, gaining access to a field dataset is a prerequisite for doing field work. Many datasets are publicly available such as government-collected data (e.g., Bureau of Labor Statistics and National Center of Education Statistics) and popular survey studies (e.g., National Longitudinal Survey of Youth and the General Social Survey). Other datasets can be easily obtained upon request such as hospital and voting records from states. Other common methods for obtaining data include scraping information from online sources using a web-scraping program, requesting data from government agencies using the Freedom of Information Act, or self-administering a survey or collecting data through observation. Lastly, many of the best field datasets are obtained through building a relationship with a particular company. For example, the wholesale car dataset that we used for the number-processing paper was provided to us directly through the company that runs the wholesale auctions. Another example of obtaining data directly from a company was a classmate and coauthor of mine who sent letters to more than one hundred independent video stores requesting data on video rentals. Only one store responded to his letters, but it only takes one. More and more companies are happy and willing to share data—especially if they think that the research may inform their decisions in a meaningful way.

An important question related to studying field data is whether the idea for a project comes before or after obtaining data. As the two motivating examples in this article illustrate, both methods of research are possible. The number-processing paper discussed above was an idea that spawned after already having access to the wholesale car auction data. The convertible paper, on the other hand, was an idea where the data were needed to be found in order to answer the question.

Gaining access to interesting data can be an arduous task, but one with a potentially very high payoff.

3.2. Graphically analyze the data

One of the great things about big datasets is that a researcher can graphically explore the raw data in order to better understand the phenomenon in question. Trying to show graphical evidence of a psychological concept is not only an effective way to present results but it also helps inoculate the researcher from making silly mistakes. Immediately running regressions on a large dataset can oftentimes result in misleading findings due to functional form assumptions or endogeneity. Graphically exploring the data can help eliminate some of these easy-to-make mistakes.

In the number-processing paper discussed above, our key finding can be shown by simply graphing the raw data.[3] In Fig. 1 below (a replication of a figure presented in the original paper), we plot the average price of cars sold in 500-mile bins from 1,000 miles to 125,000 miles.[4] As can be seen in the figure, there are clear discontinuities in prices at most of the 10,000-mile marks.[5] The fact that the dots in the figure often move in pairs provides graphical evidence of discontinuities at 1,000-mile marks as well (since each dot is a 500-mile bin, two dots represent a 1,000-mile shift).

The figure for the number-processing paper is a fairly obvious figure to make. In other papers, however, it is not as obvious how one should go about presenting the results graphically. Usually with sufficient thought, a graphical representation can be produced. For example, in the convertible paper discussed above, we presented simple scatter plots that tried to show the relationship between abnormally warm weather and abnormal car purchases. For example, the figure below plots the "residual convertible percentage" on the vertical axis. This variable represents how many more or fewer convertibles sold (as

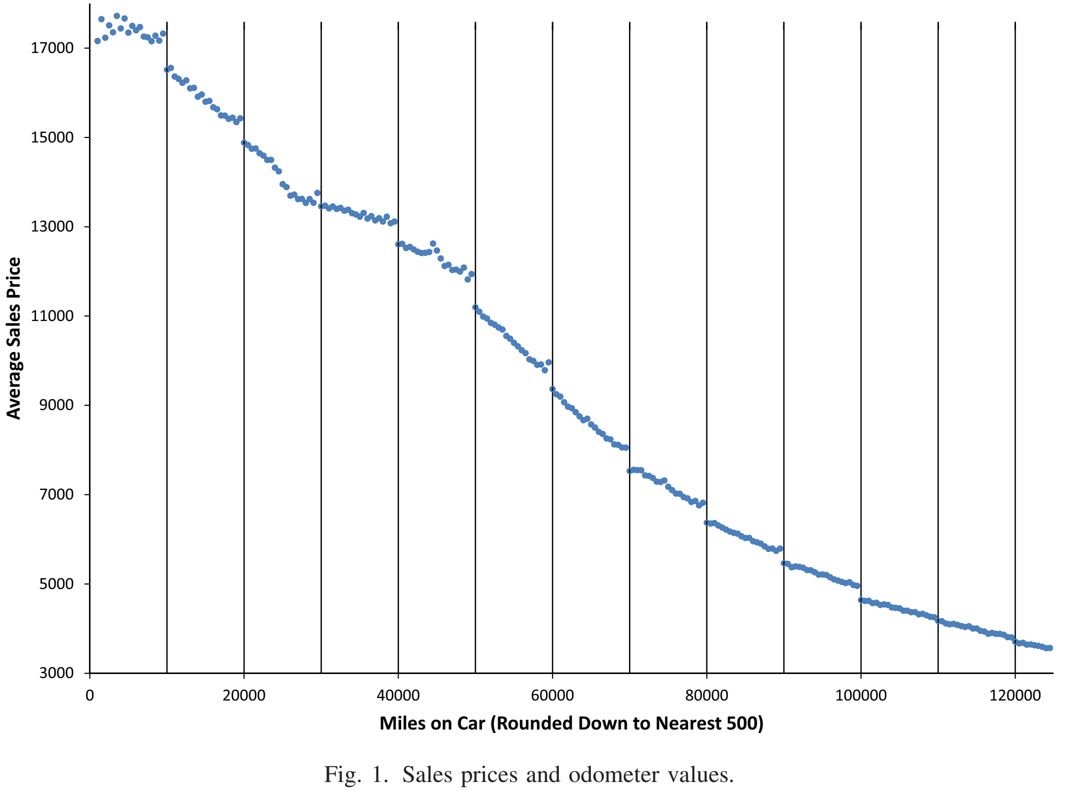

Fig. 1. Sales prices and odometer values.

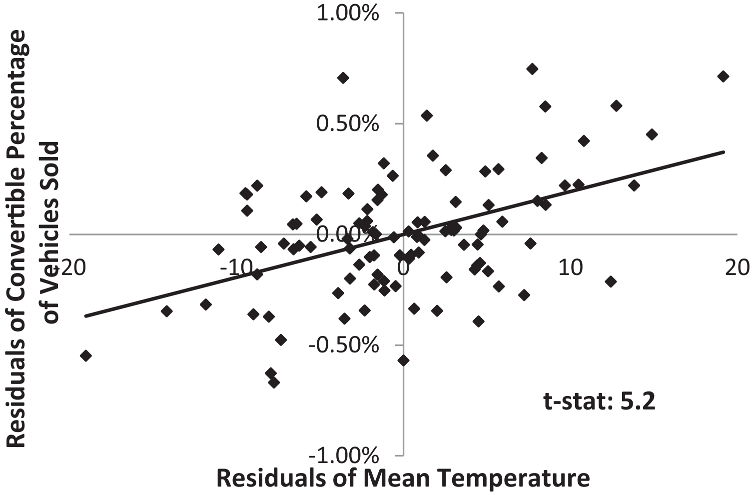

Fig. 2. Convertible sales and residual temperature.

a fraction of total cars sold) in a given week than is typically sold in that week of the year. The horizontal axis plots the variable "residual temperature." This variable is how much warmer or colder the temperature was in a given week relative to the typical temperature during that week of the year. As can be seen in the scatter plot below, when temperatures are abnormally high, the fraction of cars sold that are convertibles is abnormally high. There is a fairly strong correlation between abnormal temperature and abnormal convertible sales (Fig. 2).

Graphically showing evidence for an effect can go a long way to convincing both oneself and the reader that data indeed support the hypothesis.

3.3. Rule out alternative "rational" explanations

It is not easy to find compelling evidence of a psychological effect in field data that cannot also be explained by a different (and oftentimes "rational") explanation. Without the control that the laboratory brings, there are usually fairly significant alternative explanations that must be addressed. Once again, let's turn to our two motivating examples. In the number-processing paper, alternative explanations that we addressed in the paper included selection on observables or unobservables in terms of car type around the 10,000-mile thresholds, warranties, published price information (e.g., Kelly Blue Book), and odometer tampering. Each of these alternative explanations were addressed in turn and oftentimes, additional analyses of the data were required to shed light on whether these alternative explanations could explain our key findings.

Similarly, for the convertible paper, we had to rule out alternative "rational" explanations that included shifts in the timing of purchase (people who were planning to buy a convertible may be more likely to shop on a warm day), the possibility that warm days provided consumers a chance to test drive a convertible, and the possibility that these effects are driven by the dealers rather than by the buyers. Each of these explanations had to be discussed in turn, and we were able to rule them out as the primary cause of the effects that we find.

3.4. Discuss alternative psychological explanations

Not only can alternative "rational" explanations exist, but alternative psychological explanations other than the motivating psychology could explain the results. For example, in the number-processing paper, it could be that people are inattentive when processing numbers, or there could be a categorical thinking effect where a 79,000-mile car just feels different than an 80,000-mile car. Similarly, in the convertible paper, while projection bias can explain the findings, a simple model of salience may also be able to explain the findings. Similarly, mood effects and hyperbolic time discounting could also come into play.

Oftentimes, clues in the data can help tease apart these various psychological mechanisms. For example, we can reasonably rule out mood effects in the convertible paper by showing that the warm weather does not result in an increase in other sporty and or expensive cars sold—just in convertibles sold. Similarly, we are able to rule out hyperbolic time discounting by calibrating how hyperbolic individuals would have to be in order for that theory to explain our results (we find that the amount of time discounting would have to be far more extreme than current estimates). However, sometimes it is not possible to rule out all alternative psychological theories, and one has to be up front about the potential for multiple underlying mechanisms driving the effects.

One strategy that is sometimes effective can be to run a lab experiment to complement the results in the field data and to explore the mechanism in more detail. For example, in our number-processing paper, we ran a laboratory experiment that involved a recall task to help shed light on how left-digit bias might play out in a hypothetical car-shopping experience. We asked consumers to consider several different hypothetical car purchases and gave them several characteristics of each car including the odometer value. We then asked them to choose which car they would purchase. After making the hypothetical purchase decision, we asked them to recall the mileage of each of the cars they considered. If the left-digit bias was a result of categorical thinking, then we would predict that participants would have an unbiased recall of the mileage (69,000 just "feels" different than 71,000). If the bias is one of inattention, then we would predict that participants would systematically fail to pay attention to non-left digits and therefore be systematically biased in their recall in odometer values. This laboratory experiment provided support that the left-digit bias was being driven by inattention as opposed to categorical thinking.

Is it possible to discover "new" psychology using field data as opposed to simply applying psychology and trying to distinguish between various existing theories that could be driving the field result? To this point, the vast majority of field evidence of psychology is about simply exporting current psychological theory and applying it to field settings. Furthermore, the importance to psychology of understanding the underlying mechanisms for behavior make field work less helpful for fleshing out a new psychological theory. However, this does not mean that naturally occurring data cannot be used to aid in the discovery of new psychology. As an example, Madrian and Shea (2001) found strong evidence that despite the large stakes, individuals tend to set their savings rate for their 401k plans at the default savings rate. This field evidence was consistent with previous psychological theories (e.g., present-biased preferences, status quo bias), but the exact mechanism causing this behavior was not well understood. Given the importance of the topic, however, this field evidence has led to an increased interest in using laboratory designs to better understand the psychology behind defaults—resulting in the development of new psychological theory in this area (e.g., Dinner, Johnson, Goldstein, & Liu, 2011; McKenzie, Liersch, & Finkelstein, 2006; Tannenbaum & Ditto, unpublished data).

3.5. *Consider the generalizability of the effect*

Economists often complain about the generalizability of laboratory findings. However, just because something is found with field data does not mean that the effect will generalize to other field contexts. It is important to consider what is unique about the field of study that might not generalize to other domains. Further, it is sometimes possible to do heterogeneity cuts of the data to shed light on whether the results are likely to generalize. For example, in the number-processing study, we spent a great deal of time trying to determine who exactly had left-digit bias. The wholesale market is made up of experienced sellers and experienced buyers. However, it is possible that these experienced buyers (who will ultimately sell the cars they purchase to final retail customers) are simply catering to the biases of their final customers. For example, they may overpay for a car with 69,000 miles on it because they themselves did not pay enough attention to the number 9 in 69,000, or they may overpay because they know their final retail customers who gives limited attention to such details. We explored this question in our original paper and concluded based primarily on anecdotal/survey evidence that the wholesale participants were savvy and simply catering to the biases of their final consumers. The fact that the wholesale buyers are unlikely to be biased suggests that left-digit bias might not show up in a domain where there are very experienced agents who are purchasing products for themselves (as opposed to purchasing products for biased final customers).

4. Discussion and conclusion

There is growing interest in psychology (and many other fields) to understand how big data can be used to better understand psychological phenomenon. This paper provides two recent examples where large datasets (>20 million observations each) of market transactions were used to explore how psychological biases can impact consumers. By no means are these the only two examples that exist. Rather, there appears to be a large and growing interest in using observational data in psychology.

One complaint about the two examples provided in this paper could be that neither paper actually produced new psychology. Rather, both papers used psychology that is already known and then applied it to a field setting. This is a reasonable complaint to have if one is interested in producing new psychology rather than just applying psychology. There are several responses to this concern. While the two examples shared in this paper do not generate new psychology, this does not mean that one cannot explore new psychology in field settings. It just happens to be that these two papers borrowed heavily from current psychological theories. In addition, while not exploring new psychology, the two examples in this paper do provide insights into psychology in a few ways. For example, field work can suggest which psychological concepts are especially powerful and robust. Clearly, left-digit bias and projection bias must be strong and important human biases in order to show up in data where consumers have many competing motivations. Thus, the fact that these biases are strong enough to show up in field data suggests that psychologists should feel more comfortable exploring these particularly biases in more detail—given their importance. Further, field work can suggest possible moderators for known psychological effects, as well as boundary conditions, and the degree of individual differences.

There is also clear value to linking studies using naturally occurring data and laboratory experiments. One example of such a linking is discussed above. In general, laboratory studies are very good at testing for the internal validity of a psychological theory while field studies are better at testing for external validity. At times (as in the case above), a laboratory experiment can be used as a way to shed further light and distinguish between mechanisms for an important finding in a field setting. At other times, the laboratory experiments could be the central focus and a field setting is included in order to scale up from the laboratory setting in order to provide additional insights or external validity. Perhaps, the ideal in many cases would be to have researchers move seamlessly between the laboratory and the field in as many iterations as it takes to better understand the phenomena being studied. Moving forward, the increased use of naturally occurring data can hopefully create a powerful combination between the laboratory and the field to aid in the study of psychology.

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Notes

1. Behavioral economics also provides many examples of how psychology and field data can interact. Behavioral economics is a field that has emerged which tries to incorporate psychological insights into economic models and analyses. For an excellent review of the field work being done in behavioral economics, see DellaVigna (2009).
2. This hypothesis is related to the literature on 99-cent pricing (Anderson and Simester, 2003; Basu, 1997; Thomas and Morwitz, 2005).

3. Of course, we follow-up this graphical analysis with a more sophisticated analysis which allows us to estimate parameter values and standard errors for the effects of interest. For example, we run a regression of the final auction price for a car on a set of fixed effects for car types (make, model, body, age, etc.), a high-ordered polynomial for miles, and dummy variables for a car having an odometer value being larger than a 10,000-mile mark. The coefficient on these 10,000-mile mark dummy variables allows us to quantify the effect.
4. For example, the first dot represents the average price for cars sold that had between 1,000 miles and 1,500 miles. The second dot represents the average price for cars sold that had between 1,500 miles and 2,000 miles.
5. At a few place, the discontinuities do not show up (e.g., 30,000-mile mark). Most of these places, however, do show discontinuities in prices after controlling for the type of vehicles that show up in this market place at different miles. For example, it ends up that the cars just to the left of the 30,000-mile mark are often very different than the cars just to the right of the 30,000-mile mark due to many leases that end at 30,000 miles. Thus, once the car type is controlled for, the 30,000-mile discontinuity looks very similar to the other discontinuities in the figure.

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