Summer 2011

Exploring the relationship between knowledge and anchoring effects: is the type of knowledge important?

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EXPLORING THE RELATIONSHIP BETWEEN KNOWLEDGE AND ANCHORING EFFECTS: IS THE TYPE OF KNOWLEDGE IMPORTANT?

by

Andrew Robert Smith

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Psychology
in the Graduate College of
The University of Iowa

July 2011

Thesis Supervisor: Professor Paul D. Windschitl

ABSTRACT

Numeric estimates are influenced by a variety of factors including a person's knowledge and the presence of numeric anchors. In general, greater knowledge leads to more accurate estimates and the presence of anchors decreases accuracy. This dissertation is focused on the relationship between these two factors. At an intuitive level, it seems that increased knowledge should lead to a decrease in anchoring effects. Unfortunately, the research on knowledge and anchoring is quite mixed. This dissertation describes four studies—the first three were experimental and the last was correlational—that addressed two primary questions: 1) Does knowledge level moderate anchoring effects such that greater knowledge in a domain is associated with smaller anchoring effects? 2) Does this relationship depend on the type of knowledge one has? Studies 1 and 2 provided an answer to the first question. In Study 1, participants who studied a list of country populations—i.e., high knowledge participants—were less influenced by anchors than participants who learned irrelevant information. In Study 2, those participants who studied a list of new car prices were less influenced by anchors than participants who learned irrelevant information. In Study 3, participants learned information designed to influence different types of knowledge. The results of Study 3 supported the prediction that only those participants in conditions that increased metric knowledge—and not mapping knowledge—would exhibit reduced anchoring effects. Finally, in Study 4, participants' knowledge was measured and compared to their anchoring effects. Contrary to expectations, none of the knowledge measures were related to the participants' anchoring effects. Theoretical and practical implications, as well as reasons why the last study was not consistent with the first three, are discussed. Taken together, these studies indicate that both the amount and type of knowledge one has are important in determining one's susceptibility to anchoring effects.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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Numeric estimates are influenced by a variety of factors including a person's knowledge and the presence of numeric anchors. In general, greater knowledge leads to more accurate estimates and the presence of anchors decreases accuracy. This dissertation is focused on the relationship between these two factors. At an intuitive level, it seems that increased knowledge should lead to a decrease in anchoring effects. Unfortunately, the research on knowledge and anchoring is quite mixed. This dissertation describes four studies—the first three were experimental and the last was correlational—that addressed two primary questions: 1) Does knowledge level moderate anchoring effects such that greater knowledge in a domain is associated with smaller anchoring effects? 2) Does this relationship depend on the type of knowledge one has? Studies 1 and 2 provided an answer to the first question. In Study 1, participants who studied a list of country populations—i.e., high knowledge participants—were less influenced by anchors than participants who learned irrelevant information. In Study 2, those participants who studied a list of new car prices were less influenced by anchors than participants who learned irrelevant information. In Study 3, participants learned information designed to influence different types of knowledge. The results of Study 3 supported the prediction that only those participants in conditions that increased metric knowledge—and not mapping knowledge—would exhibit reduced anchoring effects. Finally, in Study 4, participants' knowledge was measured and compared to their anchoring effects. Contrary to expectations, none of the knowledge measures were related to the participants' anchoring effects. Theoretical and practical implications, as well as reasons why the last study was not consistent with the first three, are discussed. Taken together, these studies indicate that both the amount and type of knowledge one has are important in determining one's susceptibility to anchoring effects.

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INTRODUCTION

What is the minimum amount of money I am willing to accept for my car?

Have I consumed more than 2,000 calories today?

How long will it take to drive from Chicago to Des Moines?

Is 30 minutes enough time to bake these brownies?

The above questions exemplify the regularity with which people make numeric estimates. A large body of research has demonstrated that, while people can be fairly accurate when making numeric estimates, these estimates are often influenced by a variety of factors including a person's domain-specific knowledge, mood, motivation, the availability of new information, and the application of heuristics (e.g., Brown & Siegler, 1993; Englich & Soder, 2009; LaVoie, Bourne, & Healy, 2002; Simmons, LeBoeuf, & Nelson, 2010). Brown and Siegler (1993), for example, demonstrated that participants' estimates of country populations were influenced by their domain-specific knowledge (e.g., industrialized countries are often more populated than undeveloped countries) as well as heuristics relating to the familiarity with the counties (i.e., people gave higher estimates to countries they were more familiar with, although their estimates were no more accurate for the familiar countries).

The studies described in this dissertation were designed to test the influence of two factors that have been previously shown to influence numeric estimates—level of knowledge and numeric anchors. Specifically, I examined whether high-knowledge participants are less influenced by numeric anchors than their low-knowledge counterparts. The studies also tested whether the type of knowledge one has moderates the relationship between knowledge and susceptibility to anchoring effects.

Anchoring Effects in Numeric Estimation

In their classic study on anchoring effects, Tversky and Kahneman (1974) asked participants whether the percentage of African countries in the United Nations was higher or lower than an ostensibly randomly generated number (actually predetermined to be 10% or 65%). After providing their estimate to the comparative judgment, the participants estimated the percentage of African countries in the UN. Tversky and Kahneman found that participants' estimates assimilated toward the anchor value—comparisons with 65% produced higher estimates than comparisons with 10%.

Anchoring effects have been found in a wide variety of situations including general knowledge questions (Tversky & Kahneman, 1974), real estate prices (Northcraft & Neale, 1987), criminal sentences (Englich, Mussweiler, & Strack, 2006), negotiation outcomes (Galinsky & Mussweiler, 2001), and performance ratings of university professors (Thorsteinson, Breier, Atwell, Hamilton & Privette, 2008; for a review, see Chapman & Johnson, 2002). The strength and generality of anchoring effects have led some researchers to describe them as among the most robust effects in psychology (Chapman & Johnson, 2002). Perhaps because of the generality of anchoring effects, numerous accounts have been offered to explain why people anchor on irrelevant values. These accounts can be grouped into three categories: 1) enhanced accessibility of select knowledge, 2) anchoring and insufficient adjustment, and 3) priming.

The first account suggests that anchors cause people to recruit biased pools of information (Mussweiler & Strack, 1999; Strack & Mussweiler, 1997; see also Chapman & Johnson, 1999). Mussweiler and Strack explain anchoring effects using their Selective Accessibility model. Their model assumes that when participants compare the target estimate to an anchor, they first test whether the target is equal to the anchor value. For example, consider a situation where participants are asked to estimate the population of Germany after being exposed to a high anchor (e.g., 500 million people). Because people tend to engage in hypothesis-consistent testing (Klayman & Ha, 1987), they will likely think about information consistent with the notion that the population of Germany is relatively high. Conversely, participants who are exposed to a low anchor will recruit information that is consistent with the notion that the population of Germany is relatively low. When participants provide their absolute estimate of the population of Germany, they rely on the biased set of information that has been recruited. Therefore, estimates following a comparison with an anchor tend to assimilate toward the anchor value (i.e., comparisons with low anchors produce low judgments and comparisons with high anchors produce high judgments).

Mussweiler and Strack (2000) tested their model by having German participants compare the average price of a new car with a high or low anchor. Next, the participants completed a lexical decision task using words associated with expensive cars (e.g., Mercedes, BMW), words associated with inexpensive cars (e.g., VW, Fiesta), neutral words, and non-words. As predicted, after exposure to a high anchor, participants were faster at classifying expensive car words than inexpensive car words. The reverse was true after exposure to a low anchor—faster classifications of inexpensive car words than expensive. These results provide support for the notion that exposure to an anchor increases the accessibility of anchor-consistent knowledge.

The second account, anchoring and insufficient adjustment, assumes that the anchor provides a starting point that people use when making their judgment (Tversky & Kahneman, 1974; Epley & Gilovich, 2001; see also, Simmons et al., 2010). As information is recruited about the target, people adjust their estimate away from the anchor. These adjustments, however, tend to be insufficient (Epley & Gilovich, 2004). That is, people tend to stop adjusting once they reach a plausible estimate (Quattrone, Lawrence, Finkel, & Andrus, 1981). Because there is generally a large range of plausible estimates, adjustments that start from a low anchor stop at the lower end of this range, while adjustments from a high anchor terminate at the upper end of the range.

The third category of accounts, numeric and magnitude priming, posit that anchors prime numbers or magnitudes similar to the anchor value. For example, in one study participants' arbitrary ID numbers influenced their estimates of the number of physicians in the phone book (Wilson, Houston, Etling, & Brekke, 1996). Presumably, viewing the ID number increased the accessibility of similar numbers. When participants generated their estimates, these primed numbers were more likely to come to mind, thereby influencing their estimates (see also, Critcher & Gilovich, 2007; Wong & Kwong, 2000). The magnitude priming account is similar, but rather than priming numbers, it assumes that anchors prime magnitude concepts (e.g., "large", "small") and these concepts influence the estimates that people give (Oppenheimer, LeBoeuf, & Brewer, 2008). For example, drawing a long line caused participants give longer estimates for the length of the Mississippi River as compared to participants who drew a short line.

It should be pointed out that the relative utility of the accounts of anchoring effects appears to depend on the way in which the anchor is introduced. In most anchoring research, the anchors are provided by the experimenter and must be explicitly considered by the participant—a method described as the standard anchoring paradigm. For example, a participant might first be asked if the population of Germany is more or less than 300 million people. Then, the participant would be asked to provide their estimate of the actual population of Germany. This anchor presentation method can be contrasted with other research where the anchors are either self-generated or incidentally presented. Research investigating self-generated anchors tends to focus on questions that participants will be able to generate a value that is close to, but different from, the target value (e.g., Epley & Gilovich, 2001). For example, a participant might be asked to estimate the freezing point of vodka. Most people will first think of 32 (the freezing point of water) and then adjust their estimate from this self-generated anchor. Researchers using incidentally provided anchors will include a numeric value as an unrelated part of the question. In one study, participants estimated the likelihood that a football player would register a tackle in an upcoming game (Critcher & Gilovich, 2007). Critically, the football player's jersey number was manipulated to be either 54 or 94. While all three methods of introducing an anchor tend to produce similar results (i.e., assimilation of estimates toward the anchor values), the account that best explains the results may be different. It is often assumed that anchoring effects that arise from experimentally provided anchors are caused by a selective increase in anchor consistent information (Mussweiler & Strack, 1999; but see, Simmons et al., 2010; Wong & Kwong, 2000). Self-generated anchors are thought to be caused by anchoring and insufficient adjustment (Epley & Gilovich, 2001, 2004, 2005, 2006). Finally, incidentally provided anchors are best explained by numeric or magnitude priming accounts (Critcher & Gilovich, 2007; Oppenheimer et al., 2008).

In the studies described in this dissertation, all of the anchors were experimenter provided—that is, followed the standard anchoring paradigm. Therefore, it might seem appropriate to focus on selective accessibility accounts when making predictions about the results. Recently, however, it has become clear that the mechanisms described in the accounts can operate simultaneously and it is best to view the accounts as complementary or, at least, coexisting (Blankenship, Wegener, Petty, Detweiler-Bedell & Macy, 2008; Simmons et al., 2010; Wegener, Petty, Blankenship & Detweiler-Bedell, 2010). Blankenship et al. (2008), for example, demonstrated that under normal circumstances, a selective increase in anchor consistent information can account for anchoring effects from externally provided anchors. However, while under cognitive load, estimates given after exposure to experimenter provided anchors were driven primarily by numeric priming. Similarly, Simmons et al. (2010) argued that anchoring effects from experimenter provided anchors can be driven by both a selective increase in anchor consistent information and anchoring and insufficient adjustment.

Relationship between Anchoring Effects and Knowledge Level

Given that anchoring effects have been demonstrated across such a wide array of contexts and populations, it is important to investigate factors that might mitigate the biasing influence of anchors. One such factor might be the amount of knowledge a person has about the domain in question. At an intuitive level, it seems likely that people who have more information about a topic or domain will be less influenced by irrelevant anchors than people who do not have information about the topic. However, the theoretical and empirical evidence about the relationship between anchoring and knowledge is unclear.

Previous Theoretical Arguments Regarding Knowledge and Anchoring Effects

While none of the accounts of anchoring effects specifically make predictions about the relationship between anchoring and knowledge, researchers have made speculations based on the specifics of the accounts. For example, with regards to anchoring effects driven by a selective increase in activation, Englich (2008) proposed that knowledge would not moderate anchoring effects. Because an anchor causes a person to test the hypothesis that the target is equal to the anchor, anchor-consistent information is made accessible and will, therefore, influence later estimates. A knowledgeable judge may have access to anchor-inconsistent information, however, "…the fact that the knowledgeable judge might have alternative anchors available will not influence the target judgment, because these alternative anchors have not been related to the target" (Englich, 2008, p. 898). That is, even though information that is inconsistent with the anchor might be available to a highly knowledgeable person, it is unlike that this information will be used to form a judgment because anchor-consistent information is made most accessible by the anchor. Therefore, according to Englich, a highly knowledgeable person will recruit more information about the target than a low knowledge person, but this additional information will be biased in the direction of the anchor value. This will result in estimates from high and low knowledge people to be similarly biased by an anchor.

Other researchers have suggested that greater knowledge might lead to smaller anchoring effects. For example, Mussweiler, Strack, and Pfeiffer (2000) demonstrated that a way to combat anchoring effects is to consider anchor-inconsistent information prior to making a judgment. Because someone with a great deal of knowledge about the target would be more likely to come up with anchor-insistent information than a person with little or no knowledge about the target, we might expect anchoring effects to be smaller with high-knowledge people.

Because the theoretical arguments regarding anchoring effects and knowledge level are sparse, it is important to review the empirical evidence regarding this relationship. Unfortunately, the empirical evidence is quite mixed.

Previous Empirical Findings Regarding Knowledge and Anchoring Effects

Numerous studies have been conducted on the influence of knowledge or expertise, but the findings have been quite disparate—some found that increased knowledge leads to smaller anchoring effects while others have found equal anchoring effects between low and high knowledge individuals.

Findings Suggesting Knowledge Moderates Anchoring

As stated above, a number of studies have found that higher levels of knowledge or expertise are associated with smaller anchoring effects. For example, Wilson et al. (1996) found that participants who reported they were more knowledgeable about the number of physicians in the phone book were less influenced by anchors when estimating this value. However, it should be pointed out that the participants were asked about their knowledge level immediately after making their estimate. Their knowledge judgment could, therefore, reflect their confidence in their estimate more so than their knowledge about the topic. It is quite likely that people who felt they were adversely influenced by the anchor will also be less confident in their estimate. Therefore, it is unclear whether the results truly indicate that greater knowledge is associated with smaller anchoring effects or simply that people who showed smaller anchoring effects were more confident in their judgments.

In a study designed to assess how people adapt to changes in currency, Mussweiler and Englich (2003) assessed German participants before and after the introduction of the Euro in 2002. Before the introduction of the Euro, German participants showed larger anchoring effects when making price estimates in Euros as compared to German Marks. However, after the introduction of the Euro, the pattern was reversed such that Euro estimates were less biased than Mark estimates. Presumably, greater experience with the Euro reduced the participants' uncertainty when making price estimates and anchoring effects are assumed to be smaller when uncertainly it low.

Recently, Smith, Windschitl, and Bruchmann (2011) conducted three studies using a variety of different methodologies that all found that high knowledge participants exhibited smaller anchoring effects than low knowledge participants. In the first study, participants who were knowledgeable about football were less influenced by anchors when answering football related questions than low knowledge participants. In the second study, participants indicated their level of knowledge in a variety of domains before answering anchoring questions in these domains. When analyzed both within and between participants, higher knowledge was associated with lower anchoring effects. In the third study, American and Indian participants answered questions about American (e.g., "How many US states are west of the Mississippi River?") and Indian domains (e.g., "How old was Dr. Kalam when he became president of India?"). As was predicted, the American participants showed smaller anchoring effects for the American questions than for the Indian questions. The opposite was true for the Indian participants (i.e., smaller anchoring effects for the Indian questions and larger for the American questions). Presumably, the American (Indian) participants were more knowledgeable about the American (Indian) questions, leading them to show smaller anchoring effects for those questions.

In additional to the "direct" tests of knowledge and anchoring described above, there are also studies that provide indirect evidence that knowledge can mitigate anchoring effects. For example, in one study, participants answered anchoring questions while either under or not under cognitive load (Blankenship et al., 2008). The researchers found that the load manipulation reduced the participants' ability to recruit information about the target judgments. Therefore, if they were previously exposed to anchor-inconsistent information, the participants under load did not use this knowledge and showed large anchoring effects. Participants not under load, on the other hand, showed smaller anchoring effects as they were able to recruit their anchor-inconsistent knowledge. This study was not designed to test whether participants' level of knowledge moderates anchoring effects. However, it did show that limiting participants' ability to use their knowledge did influence the magnitude of anchoring effects. This, of course, provides evidence that knowledge is an important factor to consider when examining anchoring effects.

Findings Suggesting Knowledge Does Not Moderate Anchoring

In contrast to the research presented in the above section, a number of studies have shown that knowledge level does not moderate anchoring effects. For example, Northcraft and Neale (1987) had real-estate agents and undergraduate students estimate the actual price of a home after exposure to an anchor and found that the two groups of participants exhibited similar anchoring effects. Similarly, Englich et al. (2006) had legal experts and novices make criminal sentencing decisions after reading hypothetical decisions. The sentence length decisions of experts and novices were equally influenced by comparisons with irrelevant anchors (see also, Englich & Mussweiler, 2001; Englich, Mussweiler, & Strack, 2005; for a review of anchoring effects in judicial decisions, see Englich, 2006).

Similar results were found in one of the only studies that has manipulated participants' knowledge level. Englich (2008) had participants estimate the average price of a new midsized car sold in Germany after exposure to a high or low anchor. Before making this estimate, the participants reviewed either a series of advertisements that were about German midsize cars or about kitchens. Embedded in the advertisements were the prices of the cars or kitchens. The people who reviewed information that was relevant to the final estimate (i.e., advertisements about cars) were considered high knowledge while those participants who reviewed the irrelevant information (i.e., advertisements about kitchens) were considered low knowledge. Englich found that the high and low knowledge participants were similarly affected by the anchors—that is, knowledge did not moderate anchoring effects.

A Framework for Quantitative Estimation

Given the discrepant theoretical predictions and empirical findings, the relationship between anchoring effects and knowledge is quite unclear. In order to understand this relationship, it might be is useful to first examine how people make quantitative estimates, in general. Imagine, for example, that John is estimating the population of Germany. As described earlier, John's estimate is certainly going to be influenced by a variety of factors including his knowledge, contextual influences (e.g., anchors, motivation), and the use of heuristics (e.g., the familiarity with the target). Numerous models of quantitative estimation have been described in the literature (e.g., Brown & Siegler, 1993; Hahn & Chater, 1998; Olsson, Enkvist, & Juslin, 2006; Juslin, Olsson, & Olsson, 2003; Patalano, Smith, Jonides, & Koeppe, 2001; von Helversen & Rieskamp, 2008). These models can be loosely categorized into rule-based and exemplar based models.

Rule-based models of quantitative estimation assume that people use information about a target in a relatively controlled way (von Helversen & Rieskamp, 2009). The specific features or characteristics of a target will get weighted and then combined to produce an estimate. For example, when estimating the price of a house, a person might consider the features of the house that suggest it should be costly (e.g., nice location, large size, great amenities). The person will use this information to categorize the house into a price class (e.g., cheap, moderately price, expensive) and the average price for a house within this class will be given as an estimate (von Helversen & Rieskamp, 2008). Exemplar based models, on the other hand, suggest that estimations rely on the similarity of the target with previously encountered object (Juslin et al., 2003). The greater the similarity of the target to a previously encountered object, the closer the estimate will be to that of the exemplar.

While there may be disagreement as to the relative merits of the different models of quantitative estimation (for a comparison of these two models, see von Helversen & Rieskamp, 2009), some can be helpful in understanding how knowledge and anchors might influence numeric estimates. Brown and Siegler's (1993; see also, Brown, 2002; von Helversen & Rieskamp, 2008) framework of quantitative estimation might be particularly useful for this purpose.

An integral feature of Brown and Siegler's (1993) framework was the distinction made between two types of knowledge one might have about a target: *metric knowledge* and *mapping knowledge*. Mapping knowledge refers to how items compare with one another (e.g., Germany is larger than Norway, but smaller than the U.S.). Metric knowledge refers to general statistical properties (e.g., mean, range) that items tend to be (e.g., with a few exceptions, country populations tend to be more than 1 million and less than 500 million).

Continuing with the example of John estimating the population of Germany, one way John might go about making his estimate is to first think about how Germany compares to most other countries. That is, is Germany a small, medium, or large country? Then, John might think about the general range of country populations. Are country populations in the thousands or millions? If in the millions, is the range 1-20 million, 10-100 million, or 20-500 million? Using Brown and Siegler's (1993) terminology, John's estimate will reflect both his mapping and metric knowledge. In order for John to make an accurate estimate, he would need to be knowledgeable about how Germany relates to other countries and the general populations of countries. If either property is unknown or biased in some way, John's estimate will not be accurate.

Why Considering Type of Knowledge is Important for Anchoring Research

The previous section describes the two types of knowledge that one might have about a topic. How does this relate to research on anchoring effects? It is quite possible that people who are knowledgeable about the metric information will be more resistant to the biasing influence of anchors than a person who is knowledgeable about mapping information. For example, knowing that the population of large European countries tend to be between 40 and 140 million will help when making an estimate of the population of Germany after a comparison with an anchor. However, knowing that Germany is larger than France but smaller than Russia gives a person no insight into the actual population of Germany. Therefore, this latter person will likely be heavily influenced by comparisons with anchors. In other words, the relationship between knowledge level and anchoring effects might not necessarily depend on how much knowledge a person has, but on whether this person has the right type of knowledge.

Previous investigations into the relationship between knowledge and anchoring effects have not made a distinction between these two types of knowledge. Researchers have often measured knowledge by asking a single "knowledge" question (e.g., "How knowledgeable are you about the population of countries?"). It is quite likely that some people rated themselves as high knowledge because they were knowledgeable about metric information, while others rated themselves as high knowledge because they were knowledgeable about mapping information. Studies that compare experts to non-experts assume that experts are more knowledgeable than non-experts. While this is probably the case, it is not known what type of knowledge expertise endows a person with—metric knowledge or mapping knowledge (or both).

Finally, there is empirical evidence that even with "perfect" mapping knowledge, people will show robust anchoring effects. Ariely, Loewenstein, and Prelec (2003) organized an auction for business school students. The students were asked to indicate the maximum amount of money they would be willing to pay for numerous items (e.g., a wireless computer mouse, a rare bottle of wine) with the knowledge that if their maximum was the highest of all the students, they would win the auction and pay that amount for the item. Critically, before providing an exact estimate of their maximum willingness-to-pay (WTP), the students were asked to compare their maximum WTP to the last two digits of their social security number. Consistent with other anchoring research, the students' WTP estimates assimilated towards the last two digits of their social security numbers. The students' estimates, while biased, were also ordered sensibly. For example, people whose last two digits were high tended to report willing to pay more for a wireless computer mouse than people whose last two digits were low. At the same time, people virtually always reported being willing to pay more for a wireless keyboard than a wireless mouse, regardless of their social security number (a similar pattern was found for rare vs. average bottles of wine). Presumably, the students had a good idea that a keyboard costs more than a mouse (i.e., they had good mapping knowledge), but they still showed robust anchoring effects because they did not know how much wireless computer accessories tend to cost (i.e., they had poor metric knowledge). This research suggests that having good mapping knowledge does not mitigate anchoring effects. However, the study did not explicitly test this idea, nor did it investigate whether increased metric knowledge might help people overcome the biasing influence of anchors. Therefore, the studies described below were designed to test whether different types of knowledge differentially influence anchoring effects.

Overview of Current Studies

This dissertation describes four studies that were designed to address two primary questions. First, does knowledge level moderate anchoring effects such that greater knowledge in a domain is associated with smaller anchoring effects? Second, does the type of knowledge one has matter or are all types equally useful at reducing anchoring effects?

Of the four studies conducted, three experimentally manipulated the participants' knowledge level, while the other one was a correlational design. Using both experimental and correlational studies was important as it allows for the drawing of causal conclusions (e.g., "Increased knowledge causes decreased anchoring effects") as well as allows for the investigation of these effects in the "real world."

Study 1 was designed to test the first research question. That is, does knowledge moderate anchoring effects? This study was conducted in two phases—a learning and testing phase. During the learning phase, the participants learned information that was either relevant or irrelevant for their later estimates. This created a high and low knowledge group. During the testing phase, the participants made estimates after exposure to high and low anchors. The primary analysis, of course, tested whether the high knowledge participants exhibited smaller anchoring effects than the low knowledge participants. To preview the results of Study 1, high knowledge participants were, in fact, less influenced by the anchors than low knowledge participants.

Study 2 was a conceptual replication of Study 1, as well as provided an opportunity to test one reason why a previous study that manipulated knowledge (i.e., Englich, 2008) found that knowledge level did not moderate anchoring effects. As described earlier, before making estimates about the average price of a new midsized sedan, Englich (2008) had participants study advertisements that were relevant or irrelevant to their estimates. The materials and procedures in Study 2 were modeled after this study. As such, the participants in Study 2 provided an estimate of the average price of a new midsized sedan sold in the U.S. Like the previous study, in the learning phase, the participants saw information about was relevant or irrelevant to their later judgment. The primary difference between Study 2 and the study conducted by Englich was to include a condition that stressed the importance of carefully reviewing the information in the learning phase. Because the topic domain is one that people are at least somewhat familiar with, it is possible that people might not spend much time or effort reviewing the information presented during the learning phase. The prediction of Study 2 was that those people who learned the relevant information and were given the instructions encouraging them to learn the information would show the smallest anchoring effects.

Studies 1 and 2 were designed to experimentally test whether knowledge moderates anchoring effects. The second goal of the studies in this dissertation was to assess whether the type of knowledge one has is important. In Study 3, the influence of the different types of knowledge was tested by manipulating participants' level of one knowledge type—metric or mapping—but not the other. It was predicted that having accurate metric knowledge would decrease anchoring effects. Having accurate mapping knowledge, on the other hand, was not predicted to impact the magnitude of anchoring effects. Study 3 was similar to the previous studies in that there was a learning phase and testing phase. In Study 3, however, I included three new knowledge conditions in addition to the no- and full-knowledge conditions used in Study 1. Two of these new conditions were designed to increase participants' metric knowledge while one new condition was designed to increase participants' mapping knowledge. Using this methodology, I was able to test whether the type of knowledge a person has moderates the relationship between knowledge and anchoring effects.

The final study, Study 4, used a slightly different methodology. Rather than manipulating knowledge during a learning phase, the participants' knowledge about the topic was measured. This allowed me to examine the relationship between participants' knowledge and anchoring effects. This is similar to most previous research examining this knowledge and anchoring. Critically, however, I did not simply use a single subjective knowledge measure (as was done in the past), I measured participants' metric, mapping, and subjective knowledge. I expected that metric knowledge would better predict participants' anchoring effects as compared to mapping knowledge and subjective knowledge estimates.

CHAPTER 1

FULL VS. NO KNOWLEDGE

Given the discrepant findings of previous investigations into the relationship between knowledge and anchoring, Study 1 was designed to test a paradigm that could be used to experimentally manipulate knowledge level and assess anchoring effects. In order to be able to draw causal conclusions (e.g., "Increasing knowledge leads to a decrease in anchoring effects"), an experimental design must be used. However, the only experiment that has manipulated knowledge and investigated the impact on anchoring effects failed to find a difference between high and low knowledge participants (Englich, 2008). In that study, the participants estimated the average sale price of a midsized German car after learning the sale prices of five midsized cars (high knowledge) or the price of five kitchens (low knowledge). Because the study involved making estimates about a value that the participants certainly had some knowledge about, it is unclear whether the manipulation actually created high and low knowledge groups. The domain used in Study 1—the populations of African countries—is one that most people have very little knowledge about (Brown & Siegler, 1993; Brown, Cui, & Gordon, 2002). Therefore, providing participants with a learning phase should be quite effective in increasing their knowledge about the topic area.

The procedures of this study were borrowed from research on *seeding the knowledge base* (e.g., Brown & Siegler, 1993, 1996, 2001; Friedman & Brown, 2000; LaVoie et al., 2002). Specifically, the participants completed the experiment in two phases—a learning phase and testing phase. During the learning phase, they learned information about African countries. Participants in the full-knowledge condition were shown a list of countries and their respective populations. The list was displayed in a descending order to emphasize how the countries compare to one another. Therefore, they were able to clearly ascertain metric and mapping knowledge from the list—hence the “full-knowledge” label of this condition. Participants in the no-knowledge condition were shown a list of countries and their capital cities during the learning phase. During the test phase, the participants made estimates about the populations of African countries after considering high and low anchors. It was expected that participants in the full knowledge condition would show smaller anchoring effects than participants in the no knowledge condition.

During the testing phase of Study 1, the participants made estimates about countries they saw during the learning phase as well as countries they were not exposed to during the learning phase. It might not be surprising if learning about a county’s population decreased the anchoring effects for estimates made about that country. What is, perhaps, more interesting is whether learning the population of some countries will help when making estimates about countries one has not seen before. It was quite possible that the full-knowledge condition would only show smaller anchoring effects than the no-knowledge condition for the countries that they saw during the learning phase and not for the new countries. While this was a possibility, I expected that the full-knowledge condition would show smaller anchoring effects for all country estimates—both old and new countries.

Method

Participants and Design

Fifty-two students in an elementary psychology course participated as partial fulfillment of a research requirement. The study used a 2 (knowledge condition: full vs. no knowledge) X 2 (anchor: high vs. low) X 2 (anchor order: high first vs. low first) design with knowledge and anchor order manipulated between subjects and anchor manipulated within subjects.

Materials

The participants made estimates about 24 countries split into two lists of 12 (see Appendix A). These two lists were created such that the mean and deviation of the country populations were roughly equal to one another.

Procedures

The participants were told there were two phases to the experiment. In the first phase, they were told they would have time to review information about numerous countries. The participants were informed that this information would be useful in the second phase of the study. They learned that during the second phase, they would answer questions about countries they saw in the previous phase (i.e., “old” countries) as well as countries that they did not learn about (i.e., “new” countries).

During the learning phase, participants in both the full- and no-knowledge conditions learned information about twelve countries. Approximately half of the participants saw List A during the learning phase while half saw List B during the learning phase. Participants in the full-knowledge condition were shown the list of twelve countries and their populations. The list was displayed in a descending order to emphasize how the countries compare to one another. They were, therefore, able to clearly ascertain metric and mapping knowledge from the list. Participants in the no-knowledge condition were shown the list of twelve countries and their capital cities (these pairs were displayed in a random order). Participants in both conditions had two minutes to study the information in the learning phase. A countdown timer was displayed in the bottom right of the screen informing the participants how much time remained in the learning phase.

Immediately after the learning phase, all participants indicated how knowledgeable they were about country populations and capital cities using 7-point scales (1 = not at all knowledgeable, 7 = extremely knowledgeable). The participants were asked to take what they had learned during the study into account when answering the knowledge questions. These questions served as manipulation checks.

In the testing phase of the study, the participants answered twelve anchoring questions about the populations of countries—six high-anchor and six low-anchor questions. The participants first read instructions informing them about their task. The exact instructions were:

> "You will now answer questions about the population of African countries. Some of these countries you just learned about while others will be new. Although you might not know the population of some countries, please give your best guess. It is important that you give the best estimates that you can. Before estimating the population of the countries, you might be asked whether the population is less or more than a particular value. The value that is used has been randomly determined and is completely arbitrary."

Note that the anchor values were described as having been "randomly determined" and "completely arbitrary." This was done to reduce the possibility that the anchors would be viewed as informative by the participants (Schwartz, 1994).

For each anchoring question, the participants were first asked whether the population was more or less than the anchor (e.g., "Is the population Somalia more or less than 2 million people?"). Next, the participants provided an estimate of the population of the country (e.g., "What is the population of Somalia?"). The order of the anchor questions (i.e., six high then six low, or six low then six high) was counterbalanced across participants. Importantly, half of the countries asked about in this phase were countries that the participants saw in the learning phase and the other half were new countries. The order of presentation of new and old countries was randomized for each participant. In total, the participants will saw three old and three new countries with high anchors, and three old and three new with low anchors.

Results

Subjective Knowledge Judgments

The primary analyses in this study concern how participants' anchoring effects vary as a function of the knowledge condition. Before these analyses, however, it is important to look at participants' subjective knowledge judgments and the accuracy of their population estimates to ensure that the knowledge manipulations were successful. With regards to participants' subjective knowledge judgments, as one would expect, the participants in the full-knowledge condition reported higher levels of knowledge about country populations than participants in the no-knowledge condition ($M = 3.00$, $SD = 1.24$ and $M = 1.52$, $SD = 0.67$, respectively), $t(50) = 4.84$, $p < .001$. Also as expected, participants in the full-knowledge condition reported lower levels of knowledge about capital cities than participants in the no-knowledge condition ($M = 1.97$, $SD = 1.45$ and $M = 3.22$, $SD = 1.38$, respectively), $t(50) = 3.16$, $p = .003$. These results provide evidence that the knowledge manipulation was successful, although it should be pointed out that subjective measures of knowledge may not accurately reflect actual knowledge.

Accuracy of Estimates

Before looking at the anchoring effects, I will examine the accuracy of participants' estimates; this will provide an objective measure of the success of the knowledge manipulation. To do this, I computed an Order of Magnitude of Error (OME) for each estimate such that:

$$OME = |\log10(\text{Estimated Value}/\text{Actual Value})|$$

The OME provides a measure of error that is presented as a percentage of an order of magnitude (Nickerson, 1980). Small values represent less error (greater accuracy) and large values represent more error (less accuracy). The OME measure is useful because it minimizes the effect of outliers—a common problem when studying domains that participants are unfamiliar with. For example, if the actual value is 10, estimates of 1, 5, 10, 20, and 100 will result in OME values of 1.0, 0.3, 0, 0.3, and 1.0, respectively. There are a few properties worth noting about OME values. First, because the OME is the absolute value of error, it does not indicate whether the error represents over- or underestimation. For example, note that estimates that are half and double the actual value correspond to the same OME value (i.e., .3). And finally, the OME is a ratio, so an estimate that is twice as large as the actual value will always equal 0.3, regardless of the absolute difference between the estimate and actual value (e.g., an estimate of 10 and actual value of 5 would be the same as an estimate of 100 and an actual value of 50, even though the absolute difference is 10 times as great in the latter case). In short, the OME is a measure of how much a participant's estimate deviates from the actual population of the country.

After calculating the OME for each estimate, the six OME values for estimates made about the old countries were averaged together as were the six OME values for the new country estimates. This left each participant with two measures of error, one for the old countries and one for the new countries. A 2 (knowledge condition) X 2 (country list: old vs. new) ANOVA on participants' average OME values revealed two main effects and an interaction (see Figure 1.1). Most importantly, there was a main effect of knowledge condition, $F(1, 50) = 70.04$, $p < .001$, $\eta_p^2 = .58$, indicating that participants in the full knowledge condition provided more accurate responses than participants in the no knowledge condition. There was also a main effect of country list, $F(1, 50) = 26.62$, $p < .001$, $\eta_p^2 = .35$. These two main effects were qualified by a significant interaction, $F(1, 50) = 19.31$, $p < .001$, $\eta_p^2 = .28$. As can be seen in Figure 1.1, the difference in accuracy between participants in the full knowledge and no knowledge conditions was larger when making estimates about countries that were on the list in the learning phase (i.e., the old countries) than when making estimates about countries they had not seen before (i.e., new countries). Simple effects tests revealed that the participants in the full-knowledge condition provided more accurate responses than the no-knowledge participants for both the old countries, $F(1, 50) = 101.07$, $p < .001$, and new countries, $F(1, 50) = 24.89$, $p < .001$.

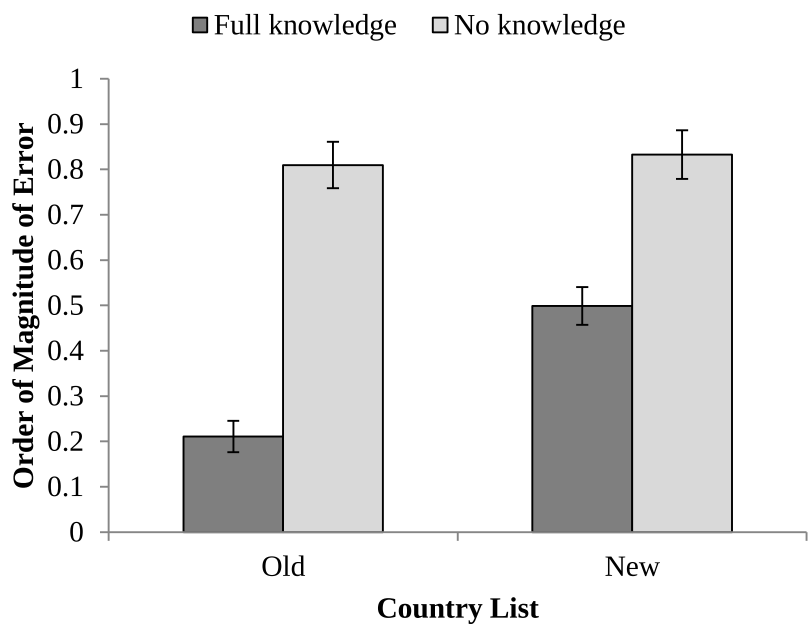

Figure 1.1 Order of magnitude of error for participants' country population estimates in Study 1. Higher values indicate greater error (i.e., less accurate estimates). Error bars represent ±1 SE.

It is clear from these results that the knowledge manipulation was successful and that the participants were able to use some of the knowledge gained about the old countries when making estimates about the new countries. OME is generally considered a measure of participants' metric knowledge (Brown & Siegler, 1993), so it would appear that the metric knowledge gained in the learning phase by the full-knowledge participants helped when making estimates about the new countries.

Whereas the OME is a form of mean-level accuracy, a different accuracy measure could assess correlational accuracy. To evaluate correlational accuracy across the experimental conditions, I calculated within-participant correlations between the participants' estimates and the actual country populations separately for the old and new countries. Finally, I computed r-to-z transformations for each correlation coefficient. A 2 (knowledge condition) X 2 (country list: old vs. new) ANOVA on participants' transformed correlations was conducted. There were, again, two main effects and an interaction (for ease of interpretation, Figure 1.2 presents the Pearson correlations rather than the transformed z-values). Participants in the full-knowledge condition showed better correlational accuracy than participants in the no-knowledge condition, $F(1, 50) = 20.53$, $p < .001$, $\eta_p^2 = .29$. Estimates made about the old countries were more accurate than estimates made about the new countries, $F(1, 50) = 19.76$, $p < .001$, $\eta_p^2 = .28$. There was also the interaction, $F(1, 50) = 20.98$, $p < .001$, $\eta_p^2 = .30$, indicating that the difference between the knowledge conditions varied depending on whether the participants were estimating the population of old or new countries. Simple effect tests revealed that estimates given by participants in the full-knowledge condition showed better correlational accuracy than participants in the no-knowledge condition for the old countries, $F(1, 50) = 28.81$, $p < .001$, but not for the new countries, $F(1, 50) = .61$, $p = .44$.

Correlational accuracy measures a person's mapping knowledge (Brown & Siegler, 1993), so it would appear that the mapping knowledge gained in the learning phase by the full-knowledge participants did not increase the rank-order accuracy when participants encountered new countries. This is in contrast to the metric knowledge that did help when making estimates about the new countries. This finding is consistent with previous research that finds that metric knowledge is generalized from old to new items, but mapping knowledge is not (e.g., Brown & Siegler, 1993, 1996; LaVoie et al., 2002). At an intuitive level this finding makes sense because learning the mapping information that, for example, Somalia is less populated than Kenya provides no insight as to how Uganda compares to these countries. However, learning the metric information that

Somalia's population is 10 million and Kenya's is 35 million does provide information as to the approximate population of Uganda.

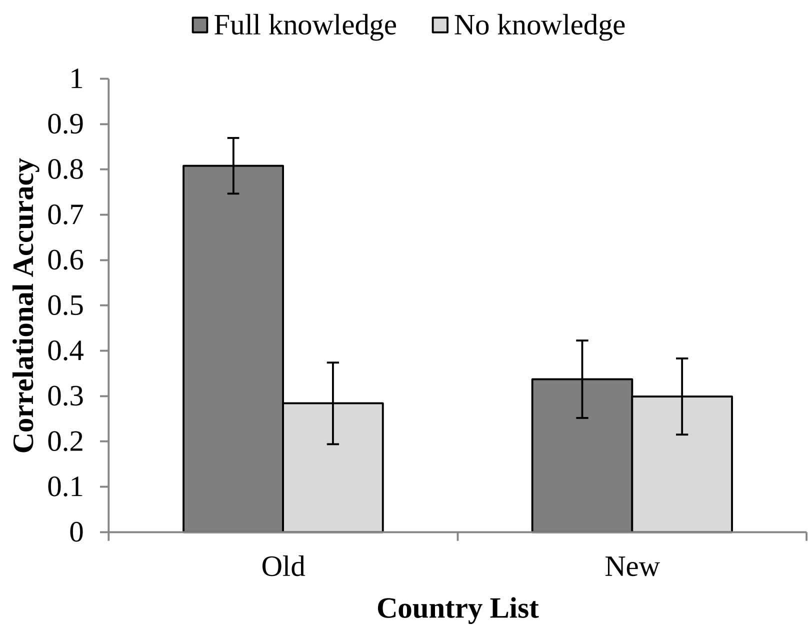

Figure 1.2 Correlations between participants' estimates and the actual population values in Study 1. Larger values represent greater accuracy. Error bars represent ±1 SE.

Anchoring Effects

The primary analyses concern how the participants' estimates were influenced by comparisons with anchors. To investigate the anchoring effects, I calculated the Signed Order of Magnitude Error (SOME) for each estimate. The SOME is defined as:

SOME = log10(Estimated Value/Actual Value)

Unlike the OME measure, the SOME indicates whether the error represents under- or overestimation (Nickerson, 1980). For example, if the actual value is 10, estimates of 1, 5, 10, 20, and 100 will result in SOME values of -1.0, -0.3, 0, 0.3, and 1.0, respectively. That is, a negative SOME value indicates underestimation while a positive

SOME value indicates overestimation. With regards to anchoring effects, it is expected that the SOME values from estimates following low anchors will be smaller than the SOME values from estimates following high anchors.

After calculating the SOME values for each participant, I averaged together his or her three SOME values about the old countries following a low anchor, the three about the old countries following a high anchor, the three about the new countries following a low anchor, and the three about the new countries following a high anchor. This resulted in an average SOME value in each of the within subjects conditions (low anchor, old; high anchor, old; low anchor, new; high anchor, new). A 2 (knowledge condition) X 2 (country list) X 2 (anchor) ANOVA was calculated on participants' average SOME values (see Figure 1.3). As expected, there was a significant effect for the anchor factor (i.e., a significant anchoring effect), $F(1, 50) = 133.93$, $p < .001$, $\eta_p^2 = .73$. Participants tended to give higher estimates following a high anchor than a low anchor. Critically, the anchoring effect was moderated by knowledge as signified by the Knowledge Condition X Anchor interaction, $F(1, 50) = 43.59$, $p < .001$, $\eta_p^2 = .47$. As can be seen in Figure 1.3, participants in the full-knowledge condition were less influenced by the anchors than participants in the no-knowledge condition. There was no three way interaction, $F(1, 50) = 1.20$, $p = .28$, $\eta_p^2 = .02$, indicating that the reduction in bias was not limited to country populations that were studied in the learning phase. The full knowledge participants were able to generalize the knowledge about the old countries to the new countries and that allowed them to limit the biasing influence of the anchors. This is consistent with my prediction that the full knowledge participants would show smaller anchoring effects for both the old and new countries.

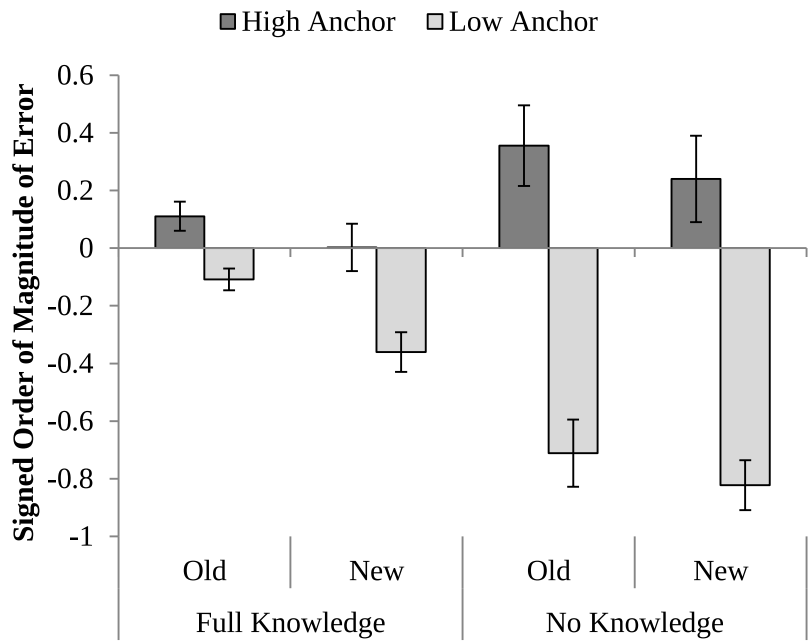

Figure 1.3 The signed order of magnitude of error for participants' population estimates following comparisons with high and low anchors in Study 1. Error bars represent ±1 SE.

Measures of Accuracy and Anchoring Effects

The above analyses revealed how OME, correlational accuracy, and anchoring effects differed across the two knowledge conditions. It is also instructive to examine the relationship between participants' anchoring effects and the two measures of accuracy (see Table 1.1). Overall, the correlations reveal a sensible pattern of results; decreases in participants' accuracy tended to be associated with increases in anchoring effects. Specifically, as OME increased or correlational accuracy decreased, participants' anchoring effects increased. The correlations also show that correlational accuracy and OME were, for the most part, related to each other. This is perhaps not surprising being that the knowledge manipulation influenced both types of knowledge and, therefore, both types of accuracy.

Table 1.1 Bivariate correlations between measures of accuracy and anchoring effects.

	OME (overall)	OME (old list)	OME (new list)	CA (overall)	CA (old list)	CA (new list)	Anchoring Effect (overall)	Anchoring Effect (old list)	Anchoring Effect (new list)
OME (overall)	-	.95***	.91***	-.49***	-.60***	-.23	.54***	.60***	.37**
OME (old list)		-	.73***	-.48***	-.68***	-.14	.62***	.71***	.41**
OME (new list)			-	-.42***	-.40***	-.30**	.35*	.37**	.26
CA (overall)				-	.85***	.77***	-.53***	-.51***	-.46**
CA (old list)					-	.38**	-.60***	-.62***	-.47***
CA (new list)						-	-.28*	-.25	-.27*
Anchoring Effect (overall)							-	.93***	.91***
Anchoring Effect (old list)								-	.69***

Note: CA = Correlational accuracy. *p < .05, **p < .01, ***p < .001

Subjective Knowledge Judgments and Anchoring Effects

I conducted a number of analyses to examine the relationship between participants' subjective knowledge judgments and their anchoring effects. A bivariate correlation revealed that these two variables were negatively correlated with one another, $r(52) = -.36$, $p = .008$. That is, participants who reported being knowledgeable about country populations tended to show smaller anchoring effects than participants who reported not being knowledgeable. It is possible that subjective knowledge judgments are related to anchoring effects. However, it is perhaps more likely that the reason subjective knowledge was related to anchoring effects in this study is because the knowledge manipulation used to create the full and no knowledge conditions influenced both the participants' subjective knowledge judgments and their anchoring effects. To test this idea, I conducted a regression analysis using participants knowledge condition (0 = no knowledge, 1 = full knowledge) and their subjective knowledge measure to predict their anchoring effect. This analysis revealed only a significant effect of the knowledge condition, $\beta = -.701$, $t(51) = 5.55$, $p < .001$. The effect of participants' subjective knowledge judgment was not significant, $\beta = .03$, $t(51) = 0.27$, $p = .79$. In other words, when controlling for participants' subjective knowledge judgment, the knowledge condition still predicted their anchoring effect. On the other hand, when controlling for the participants' knowledge condition, their subjective knowledge judgment did not predict their anchoring effect.

Another analysis that helps to clarify the relationship between subjective knowledge judgments and anchoring effects is to run separate correlations for participants in the full and no knowledge conditions. There was a non-significant negative correlation between subjective knowledge and anchoring effects for the full-knowledge participants, $r(29) = -.26$, $p = .18$. For the no-knowledge participants, there was a marginally significant positive correlation, $r(23) = .39$, $p = .07$.

Taken together, the above analyses suggest that the negative correlation between subjective knowledge judgments and anchoring effects for the full sample of participants was likely driven by the knowledge manipulation. In fact, for the no-knowledge participants, higher subjective judgments were weakly associated with larger anchoring effects.

Additional Analyses

One finding that was interesting, albeit not critical to the goals of the current study, was that participants tended to give higher estimates for those countries that were in the list they saw in the learning phase than those that were not on the list. That is, in addition to the findings described above, the 2 (knowledge condition) X 2 (country list) X 2 (anchor) ANOVA on participants' average SOME values also revealed a main effect of country list, $F(1, 50) = 19.96$, $p < .001$, $\eta_p^2 = .29$. This effect did not interact with the knowledge condition, $F(1, 50) = 1.03$, $p = .31$, $\eta_p^2 = .02$. Recall that the countries that were old and new were counterbalanced across participants, so this result cannot be accounted for by differences between the actual country populations. This finding can, however, be explained by the availability heuristic (Tversky & Kahneman, 1974); people use the availability of or their familiarity with an item to inform judgments made about that item. Presumably, studying the list of countries increased their availability and this caused participants to give higher population estimates. Availability biases have been observed when estimating the dates for events (Friedman, 1993), estimating university tuitions (Lawson & Bhagat, 2002), making fame judgments (Jacoby, Kelley, Brown, & Jasechko, 1989), and judging the truth of various statements (Begg, Anas, & Farinacci, 1992). Most important for the current study, Brown et al. (2003, Study 2) demonstrated an availability bias for estimates of country populations.

Discussion

Study 1 clearly demonstrated that anchoring effects are moderated by knowledge. Those participants who learned a list of country populations showed smaller anchoring effects than those participants who did not learn the list. This finding is in contrast to a number of previous studies, most notably the only other study that manipulated knowledge level (Englich, 2008). This raises the obvious question as to why I found that knowledge moderates the anchoring effect while others have not found this. There were at least three differences between Study 1 and the study conducted by Englich. First, the participants in Study 1 made estimates about specific items (i.e., country populations) while Englich had the participants estimate the average of a number of items (i.e., the average price of a midsized sedan). Second, the topic area in Study 1 was one that participants were unfamiliar with whereas the participants likely were familiar with the topic area in Englich's study. And third, the participants in Study 1 were explicitly told that the information presented in the learning phase would be useful when making their later judgments. In contrast, Englich simply had the participants review advertisements assuming that they would process this information and be able to use it later in the study.

Study 2 was designed to test these differences. The study was modeled after the study conducted by Englich (2008), keeping the procedures as similar as possible. The participants in Study 2 estimated the average price of a new car sold in the U.S., allowing me to test whether using a familiar topic area or having people make an average estimate might be a critical difference between the studies. I also used two different types of instructions when describing the information presented in the learning phase. This allowed me to test whether instructions that encourage the participants to carefully process the information—rather than simply read advertisments—was critical in finding the relationship between knowledge level and anchoring effects.

Regardless of the exact reason as to why the results of Study 1 were different from previous research, the results clearly suggest that knowledge level can moderate anchoring effects. The importance of these findings might be limited if the high knowledge participants showed smaller anchoring effects than the low knowledge participants only for those countries that they studied during the learning phase. However, this was not the case. The high knowledge participants demonstrated decreased anchoring effects both for countries they were previously exposed to as well as countries they had not seen. In fact, the magnitude of the anchoring effects were the same for new and old countries, indicating that the decrease was not simply due to the high knowledge participants being able to recall the exact population of a few select countries. It would appear that the participants were able to generalize some of the information they learned to new countries and this knowledge helped to combat the biasing influence of anchors.

In addition to demonstrating the importance of knowledge level, Study 1 provided indirect evidence that increased metric knowledge—and not mapping knowledge—can combat the biasing influence of anchors. Recall that when making estimates about the new countries, the full knowledge participants outperformed the no-knowledge participants in terms of their OME, but not their correlational accuracy. Presumably, they were able to use the metric knowledge about the old countries they learned during the learning phase to aid in their estimates of the new countries. In contrast, the mapping knowledge they learned about the old countries did not provide any insight into the mapping information of the new countries. Therefore, with regards to the new countries, the full-knowledge participants differed from their no-knowledge counterparts in terms their metric knowledge (and not mapping knowledge). Because the full-knowledge participants demonstrated smaller anchoring effects for the new countries than the no-knowledge participants, it would appear that increases in metric knowledge were enough to decrease anchoring effects.

Relationship between Accuracy, Error, and Bias

Before describing Study 2, it is important to clarify some terms (accuracy, error, and bias) as well as explain how they might be related to one another—both in this study and in previous research. Accuracy and error generally refer to the degree with which the participants' estimates deviate from an objective standard (e.g., the actual country populations). To facilitate interpretation, in this dissertation I generally use the term accuracy when referencing measures of correlational accuracy and error when referencing OME. Often, different measures of accuracy and error are correlated with one another; this was the case in Study 1 (see Table 1.1). However, it is quite possible that manipulations that affect one type of accuracy do not impact another type (see e.g., Brown & Seigler, 1993; LaVoie et al., 2002).

In contrast to accuracy and error, the term bias refers to how the participants' estimates systematically deviate from an objective standard towards some other value (e.g., deviation toward a high or low anchor). At first glance, it might seem that accuracy would be negatively correlated with bias, and that error would be positively correlated with bias. That is, as estimates get less accurate and exhibit more error, they should also be more biased. This was the case in Study 1 (again, see Table 1.1). However, greater accuracy and less error is not always associated with less bias. In some situations, being biased leads people to be more accurate. For example, when asked to predict a romantic partner's preference, people often use their own preferences as a starting point (Hoch, 1987). When the perceiver is actually similar to their partner, their estimates are often quite accurate (Kenny & Acitelli, 2001). Encouraging the perceiver to be less biased (i.e., not project their own preference onto their partner) does not necessarily increase accuracy, because the way the perceiver was accurate was through being biased.

There are also situations where bias, error, and accuracy are relatively unrelated to one another (Bond & DePaulo, 2008; Flether & Kerr, 2010; Gagne´ & Lydon, 2004; Luo & Snider, 2009). For example, a recent meta-analysis of lie-detection studies revealed that participants' accuracy tended to be no better than chance. People were, however, biased to report that others were telling the truth more often than telling a lie. In another study, Luo and Snider (2009) found that the accuracy and bias of newlyweds' perceptions of one another were both high, yet mostly unrelated to one another. Presumably, in this situation, bias and accuracy serve different purposes and, therefore, tend to coexist.

Study 1 highlights the complex relationship between accuracy, error, and bias. For the full knowledge participants, estimates about the old countries were more accurate (higher correlational accuracy) and had less error (smaller OME) than their estimates about the new countries. This finding might, at first, seem to contradict the result that the anchoring effects were similar for the old and new countries. In other words, it might seem odd that estimates made about the old countries were more accurate than estimates made about new countries, but they were not less biased. Recall that in this study, bias is a measure of the systematic deviation towards the anchor value. Therefore, for the full-knowledge participants, even though their estimates made about the new countries were less accurate than their estimates about old countries, they were not more systematically biased in the direction of the anchors. In short, the relationship between accuracy, error, and bias is complex and can vary depending on the context of the specific studies (for a recent discussion of accuracy and bias, see West & Kenny, 2011).

CHAPTER 2

RELEVANT VS. IRRELEVANT KNOWLEDGE

Study 1 found the predicted relationship between knowledge level and anchoring effects. Prior to this study, there has been only one other study that examined the relationship between anchoring and knowledge by manipulating participants' knowledge level (Englich, 2008). In contrast to the results of Study 1, Englich failed to find a relationship between anchoring and knowledge level. As described earlier, participants in the study first evaluated advertisements about new cars or kitchens. The primary task was for the participants to estimate the cost of the average new midsized sedan sold in Germany so some were given relevant knowledge (car advertisements) while others learned irrelevant information (kitchen advertisements). This created what Englich considered high and low knowledge participants. After reviewing the advertisements, the participants were assigned to either a basic anchoring or standard anchoring condition. In the basic anchoring condition, the participants wrote high or low numbers numerous times before providing their estimate. Participants in the standard anchoring condition directly compared their estimate to a high or low anchor.

Englich (2008) found that the knowledge manipulation did mitigate basic anchoring effects, but had no impact on anchoring effects resulting from standard anchoring. Englich explained that this difference occurred because of the different mechanisms thought to produce basic anchoring and standard anchoring effect. While this might be true, it should be noted that basic anchoring effects are notoriously fragile (Brewer & Chapman, 2002). Standard anchoring effects, on the other hand, have been described as some of the most robust in psychology (Chapman & Johnson, 2002). Therefore, it seems quite possible that a relationship between anchoring (using the standard anchoring paradigm) and knowledge exists, but the knowledge manipulation used in Englich's (2008) study was not strong enough to overcome the very robust anchoring effects. Study 2 was designed to test this idea. Namely, if the knowledge manipulation was made “stronger”, would knowledge level moderate anchoring effects? If so, this would help explain the discrepancy between Englich’s (2008) findings and the results of Study 1.

In order to facilitate comparisons between Study 2 and Englich’s (2008) study, the procedures used in Study 2 were modeled after Englich’s experiment. As such, the participants in Study 2 estimated the average price of a new midsized sedan sold in the U.S. after exposure to a high or low anchor. Before making their estimate, the participants were shown information about new cars. To create high and low knowledge groups, the type of information the participants reviewed before providing their estimate was manipulated. In some conditions, they reviewed irrelevant information while in others, they reviewed information that was relevant to their estimate. The most important deviation from Englich’s study was to vary the instructions that the participants received. Some participants were given instructions that simply asked them to read the information while other participants were given instructions that encouraged them to carefully review and process the information. This was done to increase the strength of the manipulation with the prediction that reviewing relevant information would decrease anchoring effects, but only when the instructions were strong enough to encourage the participants to carefully process the information.

Method

Participants and Design

One-hundred thirty-two participants from the U.S. were recruited using Amazon’s Mechanical Turk (MTurk; for information on using MTurk for participant recruitment and experimentation, see Buhrmester, Kwang, & Gosling, 2011; Paolacci, Chandler, & Ipeirotis, 2010). The participants were paid $0.15 for their participation. This study was a 3 (knowledge condition: irrelevant, relevant-weak, relevant-strong) X 2 (anchor: high vs. low) between subjects design.

Procedure

After viewing the study information on MTurk, the participants were directed to the survey web site. All participants read general instructions describing the survey and were then directed to specific instructions that varied depending on their knowledge condition. Participants in the irrelevant and relevant-weak conditions were told that they will be given a list of cars for their reference and they should look over the list before moving on (see Appendix B for the exact instructions). Participants in the relevant-strong condition were also told they would see a list of cars, but were explicitly told to carefully review the information in the list because they would be asked questions about the cars later in the study.

Below the instructions, the participants were shown a table with the names of five new cars, a photo of each, and one additional piece of information (see Appendix C). In the irrelevant knowledge condition, the participants were given the worldwide sales figures for 2011 for each car. Participants in the relevant-weak and relevant-strong conditions were given the base price of each car. It is important to note that the values used for the base price and worldwide sales figures were the same regardless of knowledge condition. For example, participants in the irrelevant knowledge condition saw that the worldwide sales of the Chevrolet Cruze were 17,000 and participants in the two relevant knowledge conditions saw that the base price was $17,000.

After reviewing the information, all participants were told they would be answering questions regarding their thoughts about new cars. The participants were also given information about the "randomness" of the anchor values. Specifically, they were told, "For some of the questions, you might be asked to make a comparison with a specific number. The numbers are randomly determined and, therefore, completely arbitrary." Next, the participants compared the average price of a new midsized sedan to either a high ($41,100) or low anchor ($14,100) (e.g., "Do you think the average price of new midsized sedan sold in the U.S. is more or less than $14,100?"). The participants then provided an estimate of the average price of a new midsized sedan sold in the U.S. Finally, the participants were asked their age and gender.

Results

A critical component of this study is that participants who received relevant information were given instructions that did (strong instructions) or did not (weak instructions) highlight the usefulness of the information about the cars. Presumably, the strong instructions would encourage the participants to carefully review the information. In support of this is the fact that, of the participants who received relevant information, those who received the strong instructions ($M = 52.71$ seconds, $SD = 37.43$) spent more time looking at the information page than participants who received the weak instructions ($M = 38.56$ seconds, $SD = 25.12$), $t(82) = 2.04$, $p = .04$.

Anchoring Effects

To evaluate the influence of knowledge on anchoring effects, I conducted a 3 (knowledge condition) X 2 (anchor) ANOVA on the participants' estimates of the average price of a new midsized sedan.[1] This analysis revealed a robust anchoring effect, $F(1, 126) = 60.37$, $p < .001$, $\eta_p^2 = .32$. Most importantly, there was also the predicted Knowledge Condition X Anchor interaction, $F(2, 126) = 3.51$, $p = .03$, $\eta_p^2 = .05$. As can be seen in Figure 2.1, participants in the irrelevant and relevant-weak conditions

[1] In contrast to the previous study, the analyses were conducted on participants' raw estimates. Because the actual value of the average price of a new midsized sedan is not readily available, converting the participants' estimates to SOME values was not possible. It should also be pointed out that the estimates were not skewed—as was the case in Study 1—so transforming the estimates was not necessary even if it was possible.

exhibited similar anchoring effect—both of which were quite large. However, participants in the relevant-strong condition were much less influenced by the anchors. Tests of simple effects revealed robust anchoring effects for the irrelevant ($p < .001$, $\eta_p^2 = .20$) and relevant-weak ($p < .001$, $\eta_p^2 = .21$) knowledge conditions. Although much smaller, participants in the relevant-strong condition also exhibited significant anchoring effects ($p = .03$, $\eta_p^2 = .04$).

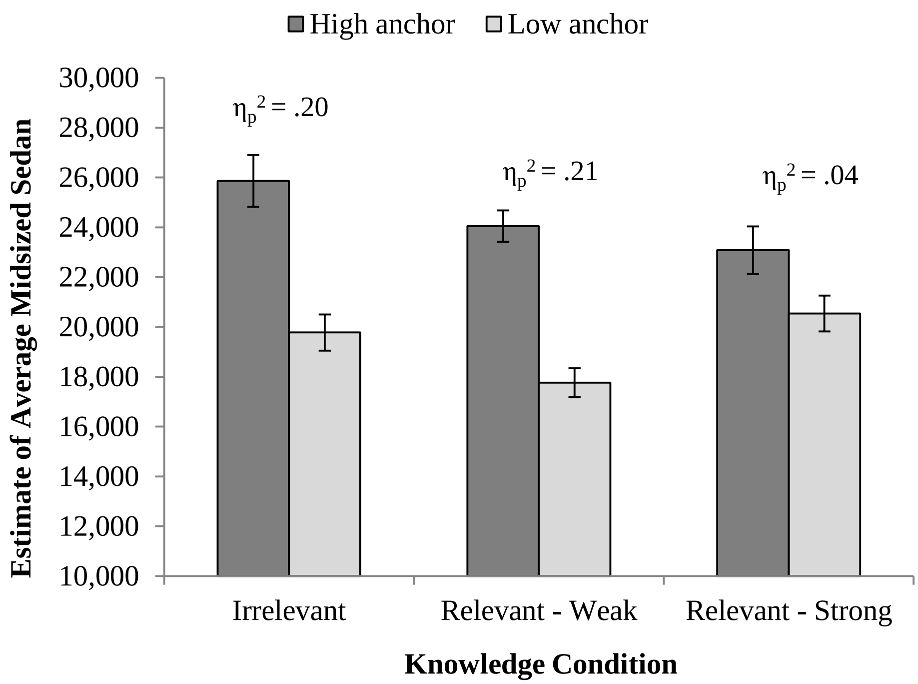

Figure 2.1 Average estimate of the price of a new midsized sedan sold in the U.S. Error bars represent ±1 SE.

Discussion

The results of Study 2 are consistent with the findings of Study 1 in that high knowledge participants were less influenced by anchors than low knowledge participants.

As predicted, the decrease in anchoring effects occurred when the participants were given relevant background information *and* they were encouraged to process this information.

In addition to supporting the claim that knowledge moderates anchoring effects, the results of Study 2 also potentially explain why previous investigations have failed to find this relationship (e.g., Englich, 2008). That is, because the influence of anchors is so strong, manipulations designed to reduce anchoring effects must be quite robust in order to be effective. The knowledge manipulation used by Englich (i.e., presenting some participants with advertisements about cars) was not strong enough to overcome the anchoring effects. Similarly, in Study 2 the participants in the relevant-weak condition exhibited virtually identical anchoring effects as those participants in the irrelevant condition. It was not sufficient to simply present these participants with information that was relevant to their later judgment. Instructions encouraging the participants to process the information were also necessary in order to help reduce the biasing influence of anchors.

One might wonder why the strong instructions were needed in order to show the moderating effect of knowledge. In other words, why was it not enough to simply provide the participants with the relevant information? One reason, as described above, is that the instructions might have motivated the participants to attend to and process the information more fully. A second, related reason concerns the topic area. Most participants were likely somewhat familiar with the price of new cars. Therefore, in order for the knowledge manipulation to be successful, it needed to increase their knowledge level beyond what they had before the study began. If a person feels they are familiar with the topic area, they might not feel it necessary to spend much time or effort in learning information.

This is in contrast to Study 1 where the participants made estimates about the populations of African countries—a topic that most people have very little knowledge about. In that study, even a small amount of information should be enough to increase the participants' knowledge. There are, of course, many other differences between the learning phases in Studies 1 and 2. Perhaps the biggest difference is that the participants in Study 2 could review the information for as long (or short) as they wanted. In Study 1, the time spent reviewing the information was controlled by the computer. Given this—and other—difference between the studies, it is impossible to know precisely what factors are necessary to find the moderating influence of knowledge on anchoring effects. However, two conclusions can be drawn from Studies 1 and 2. First, and most importantly, knowledge level plays a causal role in moderating anchoring effects. Second, finding this relationship might depend to some degree on the experimental methodology used (e.g., using strong instructions, choosing a topic area where knowledge is generally low, requiring the participants to review the information for a predetermined amount of time).

CHAPTER 3

DIFFERENT TYPES OF KNOWLEDGE

Studies 1 and 2 demonstrated that knowledge level moderates anchoring effects. However, it is not clear whether this relationship depends on the type of knowledge one has. In both studies, the knowledgeable participants (full knowledge in Study 1 and relevant-strong in Study 2) were given both metric and mapping knowledge. Study 3 again investigated the relationship between knowledge and anchoring effects, but specifically examined the impact of different types of knowledge. Study 3 was very similar to Study 1, both in terms of topic area (i.e., population estimates of African countries) and methodology. In addition to the full- and no-knowledge conditions used in Study 1, there were three more knowledge conditions—range, distribution, and rank-order knowledge. The range condition received information about the range of African countries, the distribution condition learned information about the distribution of populations of African countries, and the rank-order condition received information about how the countries compare with one another. The range and distribution conditions provided the participants with metric knowledge, but no mapping knowledge. The rank-order condition, on the other hand, provided the participants with mapping knowledge, but no metric knowledge.

The critical questions in Study 3 were whether and how the new knowledge conditions (range, distribution, and rank-order) might influence anchoring effects. There are at least three different possibilities. First, participants in all three new conditions might show anchoring effects similar to the participants in the no knowledge condition. This would indicate that to reduce anchoring effects, one must have metric and mapping information about specific countries—as was the case for the full knowledge condition. Second, all three new conditions might show anchoring effects similar to the full knowledge condition. This would indicate that receiving any information, whether it was about the metric or mapping properties of the countries, is sufficient to reduce anchoring effects. Third, the anchoring effects might vary between the three new conditions. This is the outcome that I predicted. Specifically, I expected that the two conditions that provided metric information (range and distribution) would show smaller anchoring effects than the condition that provided mapping information (rank-order).

In addition to the added knowledge conditions used in this study, I made another small, but important change. In Study 1, the high and low anchors (150 million and 2 million, respectively) were outside the range of populations presented to the high knowledge participants during the learning phase. Because of this, it is possible that the only reason the high knowledge participants were less influenced by anchors than the low knowledge participants is that they were able to reject the anchors as clearly too high or too low. Perhaps if the anchors were inside the range of countries presented during the learning phase, the high and low knowledge participants would be equally affected by the anchors. Study 3 directly tested this idea by using more moderate anchors.

Method

Participants and Design

One hundred thirty-two students in an elementary psychology course participated as partial fulfillment of a research requirement. This study was a 5 (knowledge condition: full, range, distribution, rank-order, and no knowledge) X 2 (anchor: high vs. low) X 2 (anchor order: high first vs. low first) design with knowledge and anchor order manipulated between subjects and anchor manipulated within subjects.

Materials and Procedures

Overall, the materials and procedures were similar to those used in Study 1. Specifically, the participants went through a learning phase, answered subjective knowledge questions, and then completed the testing phase.

During the learning phase, the participants were shown a list of the names of sixteen African countries along with additional information that varied as a function of the knowledge condition (see Appendix D for the list of countries used in Study 3). The full-and no-knowledge conditions were the same as in Study 1 (i.e., the full-knowledge condition saw the country names and populations while the no-knowledge condition saw the country names and capital cities). Participants in the range condition were shown sixteen country names ordered randomly and were told that all the country populations are between 3 and 85 million. Participants in the distribution condition were shown two lists, one with country names, and the other with the country populations. The country names were displayed in a random order so the participants did not know what population value went with what country. The participants were, however, able to gather the range and distribution of African countries. These two conditions provided the participants with metric knowledge about the population of African countries. The rank-order condition was shown the list of sixteen countries ordered from most to least populated but with no population values provided. This provided the participants with mapping information (i.e., how the countries compare with one another), but no metric information.

After the learning phase, participants provided four separate subjective judgments of their knowledge about African countries. In addition to the question about their general knowledge of country populations used in Study 1, the participants were also asked questions designed to assess their mapping and metric knowledge. Specifically, they were asked how knowledgeable they were about "…how African countries compare to one another in terms of their populations (for example, knowing which countries are relatively large and which are relatively small)?" and "…the specific population values that African countries tend to be?" The final subjective knowledge question asked the participants to indicate their knowledge of the capital cities of African countries.

During the testing phase, the participants made estimates about the population of the African countries after exposure to high or low anchors. In this study, the high anchors were 70 and the low anchors were 8. As stated earlier, these values are within the range of populations for the countries the participants saw during the learning phase. Because of this, the participants only made estimates about the 12 countries whose actual populations were lower than the high anchor and higher than the low anchor. The participants made 6 estimates after a low anchor and 6 after a high anchor in a blocked order. That is, they made all 6 low anchor estimates first and then all 6 high anchor estimates second, or vice versa. Finally, the participants were debriefed and thanked for their participation.

Results

Subjective Knowledge Judgments

As in Study 1, before examining participants' anchoring effects, I will first describe how the knowledge factor influenced participants' subjective judgments and the accuracy of their population estimates. This will provide evidence as to the success of the knowledge manipulation. Recall that, in addition to the judgment about their knowledge of capital cities, the participants made three separate subjective knowledge judgments designed to assess their overall knowledge, mapping knowledge, and metric knowledge. As would be expected, these three measures were correlated with one another (all $rs > .55$, $ps < .001$). The participants' knowledge judgments split by knowledge condition are plotted in Figure 3.1.

To analyze whether the knowledge condition influenced participants' knowledge judgments, each was submitted to a one-way ANOVA. As expected, each knowledge judgment differed as a function of the information the participants had learned in the first part of the study ($ps < .05$). For the general knowledge question, contrast tests revealed that the full knowledge condition reported being more knowledgeable than the range, distribution, and no knowledge conditions ($ps \leq .05$). No other differences were observed. For the mapping question, the full knowledge condition reported higher knowledge levels than the rank-order condition ($p = .02$) and the rank-order condition reported higher mapping knowledge than the other conditions ($ps \leq .01$). For the metric question, the full knowledge condition was, again, the highest ($p < .05$). Metric knowledge judgments did not differ for the other knowledge conditions. And finally, participants in the no-knowledge condition reported being most knowledgeable about capital cities ($p < .001$). This, of course, makes sense because the no-knowledge condition reviewed capital cities instead of populations during the learning phase.

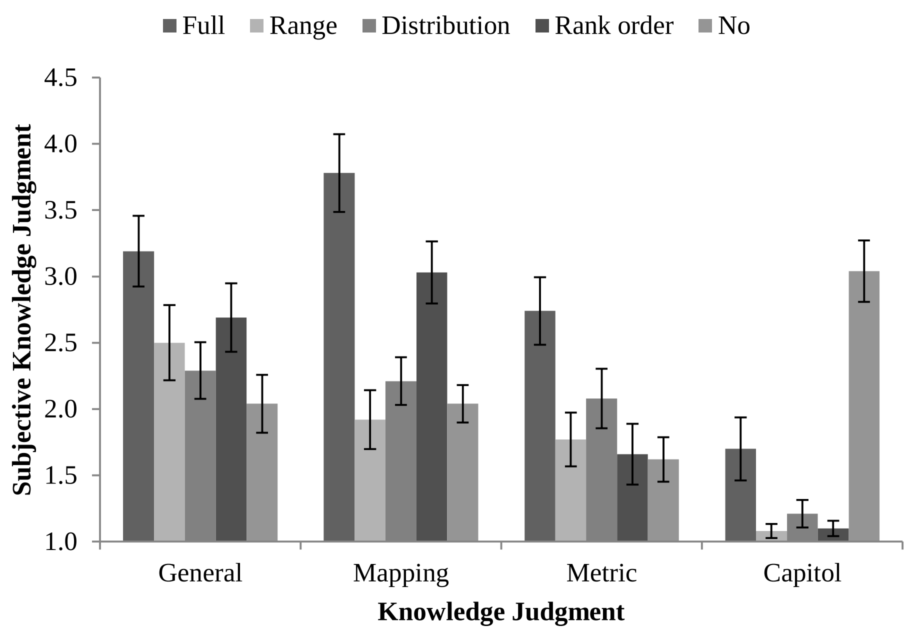

Figure 3.1 Mean of participants' subjective knowledge judgments split by knowledge condition and knowledge judgment. Error bars represent ±1 SE.

Overall, these analyses reveal that the participants were aware, at least to some degree, about the information they had learned in the learning phase. Namely, the full knowledge participants reported high levels of knowledge in three relevant judgments. The rank-order condition reported high levels of mapping knowledge relative to the no-knowledge condition. And the distribution condition reported high levels of metric knowledge (although their ratings were not significantly different from the no-knowledge condition).

Accuracy of Estimates

Evaluating how the accuracy of participants' population estimates vary as a function of the knowledge conditions will provide an objective assessment as to the success of the knowledge manipulation. Mean level accuracy was again evaluated by computing an OME value for each of the participants' estimates. As a reminder, the OME represents the amount of error in participants' estimates such that higher values indicate less accurate responses. Participants' average OME are plotted in Figure 3.2. As expected, a one-way ANOVA on participants' OME values revealed that they varied as a function of the knowledge condition, $F(4, 127) = 14.03$, $p < .001$. Follow-up contrast tests revealed that participants in the full-knowledge condition had smaller OME values than participants in the distribution condition, $t(127) = 2.25$, $p = .03$. Participants in the distribution condition had smaller OME values than participants in the range condition, $t(127) = 2.39$, $p = .02$. Participants' OME values in the range, rank-order, and no-knowledge conditions did not differ from one another ($p > .14$ for all pairwise comparisons).

As described earlier, OME is often used as a measure of people's metric knowledge (e.g., Brown & Siegler, 1993). The above analyses reveal that, relative to the no-knowledge condition, participants' metric knowledge was improved in the full and distribution conditions. Participants' metric knowledge was not affected in the range and rank-order conditions. The enhancement of metric knowledge in the full and distribution conditions is consistent with what was expected. However, I also expected that participants in the range condition would show enhanced metric knowledge relative to the rank-order and no knowledge conditions. The fact that this did not happen might suggest that learning range information is not enough to improve metric knowledge. It is possible that the participants already had a general sense of the range of country populations, so the specific manipulation did not increase the participants' knowledge beyond what they already had.

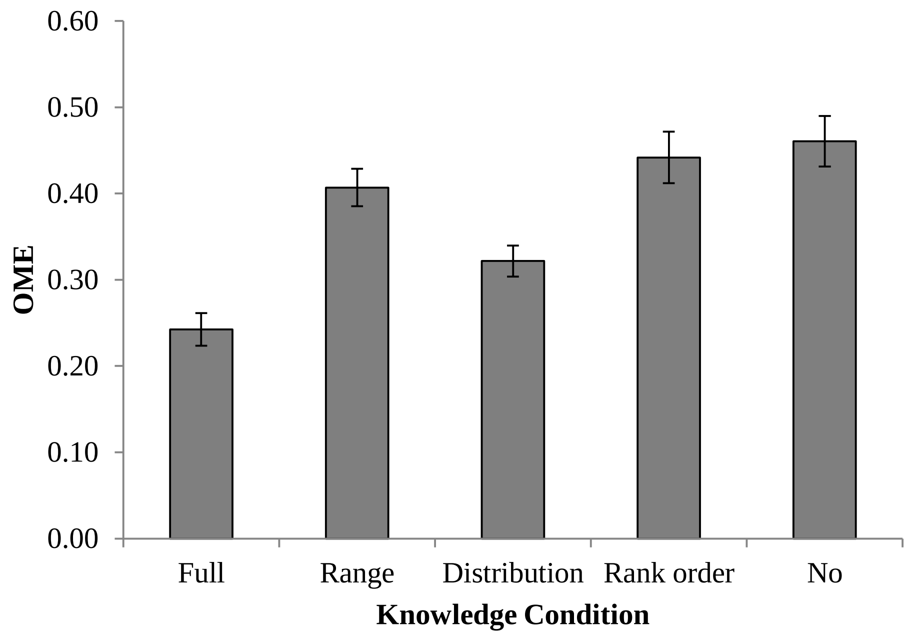

Figure 3.2 Order of magnitude of error for participants' country population estimates in Study 2. Higher values indicate greater error (i.e., less accurate estimates). Error bars represent ±1 SE.

The other form of accuracy that is of interest is correlational accuracy. For each participant, I calculated the correlation between their population estimates for the 12 countries and the actual population of the countries. Next, r-to-z transformations were performed on each participant's correlation coefficient (for ease of interpretation, Figure 3.3 presents the Pearson correlations for each knowledge condition). A one-way

ANOVA revealed that correlational accuracy varied as a function of the knowledge condition, F(4, 127) = 12.00, p < .001. Follow-up contrast tests revealed that participants in the rank order and full knowledge conditions did not vary in terms of their correlational accuracy, t(127) = 0.62, p = .54. Participants in the rank-order and full-knowledge condition exhibited greater correlational accuracy than the other three conditions (ps < .001). And finally, the correlational accuracy of participants in the range, distribution, and no-knowledge conditions did not differ (ps > .47).

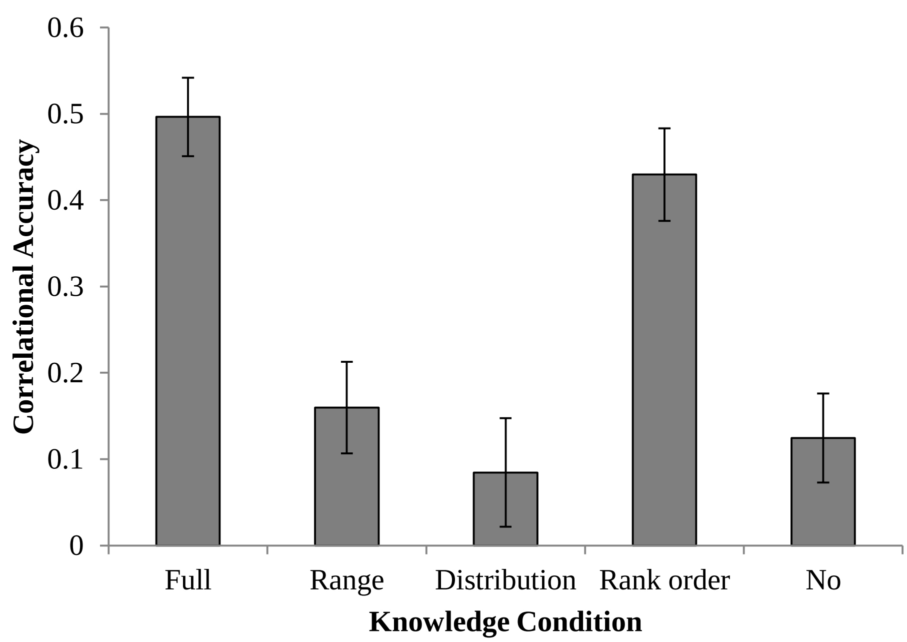

Figure 3.3 Correlations between participants' estimates and the actual population values in Study 3. Larger values represent greater accuracy. Error bars represent ±1 SE.

The above analyses reveal an expected pattern. Namely, participants' mapping knowledge, as measured by correlational accuracy (Brown & Siegler, 1993), was enhanced in the rank-order and full-knowledge conditions. Mapping knowledge was unaffected—relative to the no-knowledge condition—in the range and distribution conditions.

Taken together, these two measures of accuracy reveal that, with the exception of the range condition, the knowledge manipulations were quite successful. Specifically, participants' mapping and metric knowledge was increased in the full-knowledge condition. Participants' metric knowledge (but not mapping knowledge) was increased in the distribution condition. Participants' mapping knowledge (but not metric knowledge) was increase in the rank-order condition. Participants in the range condition did not show an improvement in either type of knowledge. Finally, it is worth noting that these two measures of accuracy were correlated with one another, $r(132) = -.29$, $p = .001$. Participants who were more accurate from a correlational sense exhibited less error in their estimates.

Anchoring Effects

The primary analyses concern how participants' anchoring effects vary as a function of the knowledge condition. In order to examine the influence of the different types of knowledge on anchoring effects, I first computed participants' SOME for each estimate and then averaged together those values following a high anchor and those following a low anchor. Next, a 5 (knowledge condition) X 2 (anchor) X 2 (anchor order) ANOVA on participants' SOME values revealed the expected main effect of anchor, $F(1, 122) = 184.09$, $p < .001$, $\eta_p^2 = .60$—higher estimate following a high anchor than low anchor. As predicted, this main effect was qualified by a Knowledge Condition X Anchor interaction, $F(1, 122) = 8.02$, $p < .001$, $\eta_p^2 = .21$. As seen in Figure 3.4, the anchoring effect (i.e., the difference between high and low anchor estimates) varies as a function of the knowledge condition. On Figure 3.4, the effect size measures for the anchoring effects are reported separately for each knowledge condition. An examination of the effect size measures, at least from a descriptive standpoint, supports the prediction that the knowledge conditions that influence metric knowledge exhibited the smallest anchoring effects. The full and distribution conditions exhibited the smallest anchoring effects. A finding that is perhaps surprising is that the rank-order condition exhibited a substantially smaller anchoring effect than the no knowledge condition (see the Discussion section below for a potential explanation of this finding).

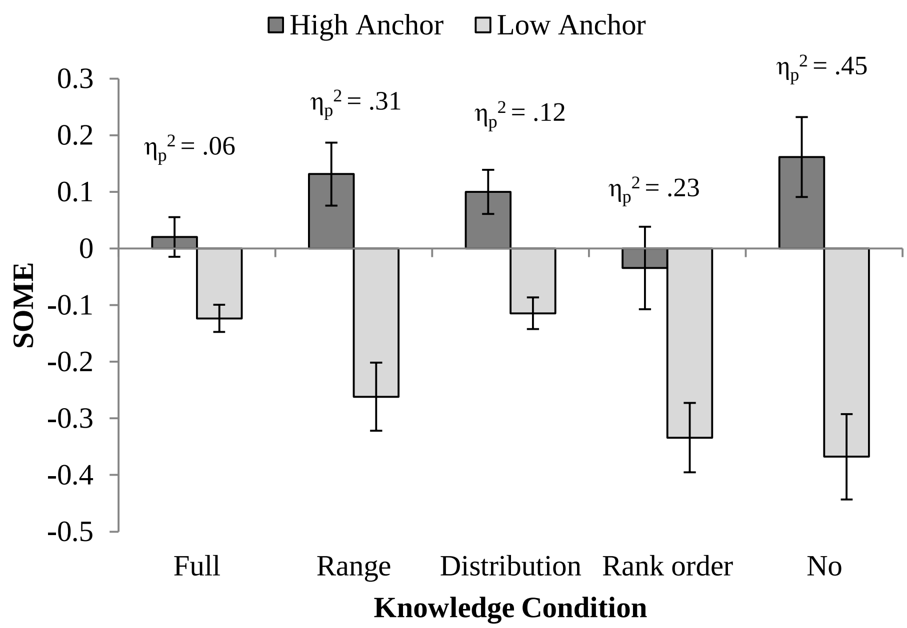

Figure 3.4 The signed order of magnitude of error for participants' population estimates for all estimates. Error bars represent ±1 SE.

The above analysis also revealed a main effect of anchor order, $F(1, 122) = 4.08$, $p = .05$, $\eta_p^2 = .03$. Participants who saw low anchors first gave, overall, lower estimates than participants who saw high anchors first. In addition to the main effects and two-way interactions listed above, there was a three way interaction, $F(4, 122) = 3.09$, $p = .02$, $\eta_p^2 = .09$.

Because anchor order produced a main effect and the three-way interaction, I analyzed the anchor condition the participants experienced first (recall that participants made 6 estimates following a low anchor and then 6 following a high anchor, or vice versa). That is, I only examined the first 6 estimates they gave and treated anchor as a between subjects factor. A 5 (knowledge condition) X 2 (anchor) ANOVA on participants' SOME values revealed a significant anchoring effect, $F(1, 122) = 77.61$, $p < .001$, $\eta_p^2 = .39$. Again, this main effect was qualified by a significant Knowledge Condition X Anchor interaction, $F(4, 122) = 4.57$, $p = .002$, $\eta_p^2 = .13$. Figure 3.5 plots participants' SOME values for their first six estimates. As before, the effect size measures for the anchoring effects are listed separately for each knowledge condition. By examining the effect size measures, it is clear that the conditions that improved metric knowledge (full and distribution conditions) showed substantially smaller anchoring effects than those that did not (the range, rank-order, and no knowledge condition). In fact, the range and rank-order conditions did not substantially differ from those participants who received no information at all. These results clearly suggest that the type of knowledge one has differentially influences one's susceptibility to anchoring effects.

The finding that the range condition showed anchoring effects similar to the rank-order and no-knowledge conditions does not fit with my original expectation. However, in light of the earlier analysis that revealed no improvement in metric knowledge for the range condition (i.e., average OME similar to the rank-order and no-knowledge condition), this pattern makes sense. Finally, it is worth noting that an analysis restricted to the distribution and rank-order conditions revealed the expected Knowledge Condition X Anchor interaction, $F(1, 49) = 6.22$, $\eta_p^2 = .11$. In other words, the group that received metric knowledge (but not mapping knowledge) exhibited smaller anchoring effects than the group that received mapping knowledge (but not metric knowledge).

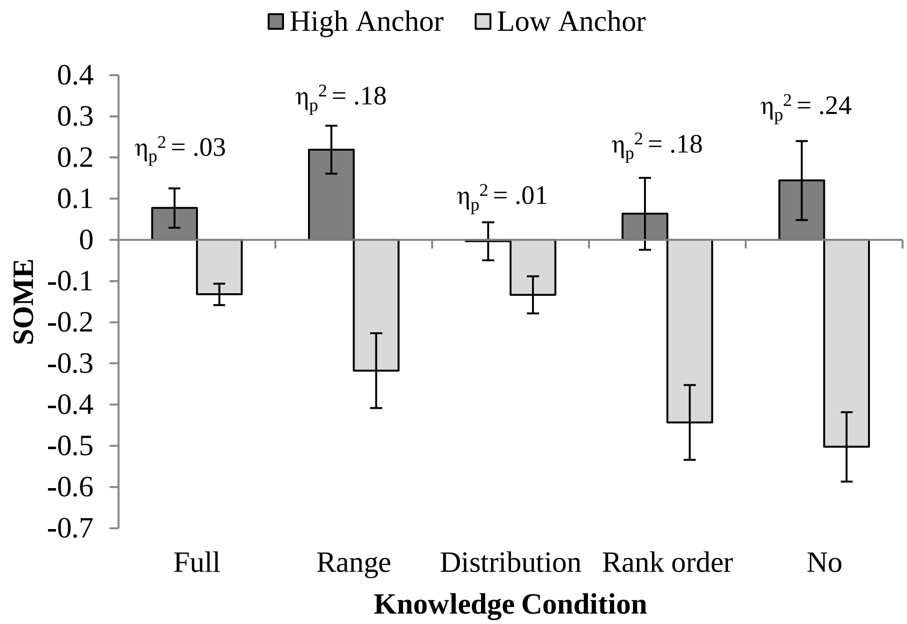

Figure 3.5 The signed order of magnitude of error for participants' population estimates for the estimates made in the first anchor condition the participants encountered. Error bars represent ±1 SE.

Measures of Accuracy and Anchoring Effects

How were the participants' measures of accuracy related to their susceptibility to anchoring effects? To address this question, I computed a regression analysis predicting participants' SOME of the first 6 estimates from their anchor condition (low or high), OME for the first 6 estimates, their correlational accuracy for the first 6 estimates, and the two two-way interaction terms. This analysis revealed main effects of participants' anchor condition, $\beta = .55$, $t(126) = 9.66$, $p < .001$, and OME, $\beta = -.28$, $t(126) = 4.17$, $p < .001$. The two interaction terms also significantly predicted participants' SOME values. First, the interaction between anchor condition and participants' OME was significant, $\beta = .31$, $t(126) = 4.71$, $p < .001$. As shown in Figure 3.6, participants who exhibited less error in their estimates (i.e., lower OME values) were less influenced by anchors. This pattern could be interpreted as demonstrating that more knowledgeable participants (those with lower OME values) exhibited smaller anchoring effects than less knowledgeable participants (those with higher OME values). However, because the OME was calculated from the anchored estimates, this pattern could also be interpreted as showing that participants who exhibited less error in their anchored estimates also exhibited smaller anchoring effects. This is perhaps to be expected as bias (anchoring effects, in this case) and error (OME) are sometimes related (although not necessarily so; West & Kenny, 2011).

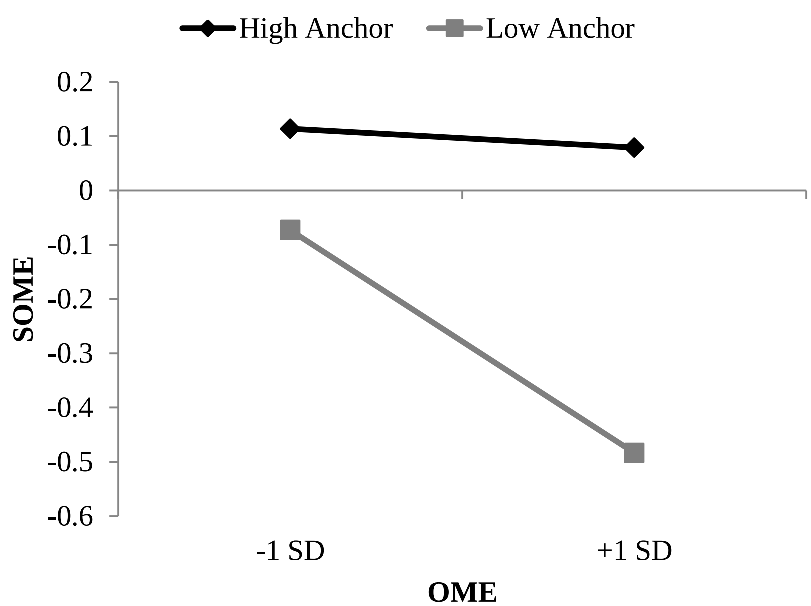

Figure 3.6 Relationship between OME and SOME for the anchored estimates split by anchor condition.

Second, there was also an interaction between anchor condition and participants' correlational accuracy, $\beta = .16$, $t(126) = 2.67$, $p = .008$. This relationship is plotted in Figure 3.7. Interestingly, as correlational accuracy increased, participants' estimates were more influenced by anchors. That is, more accurate (correlationally) participants exhibited stronger anchoring effects. This relationship is somewhat surprisingly given that participants' correlational accuracy was negatively related to OME, r(132) = -.17, p = .05. Taken together, however, these two interactions clearly indicate that greater metric knowledge—and not greater mapping knowledge—is associated with smaller anchoring effects.

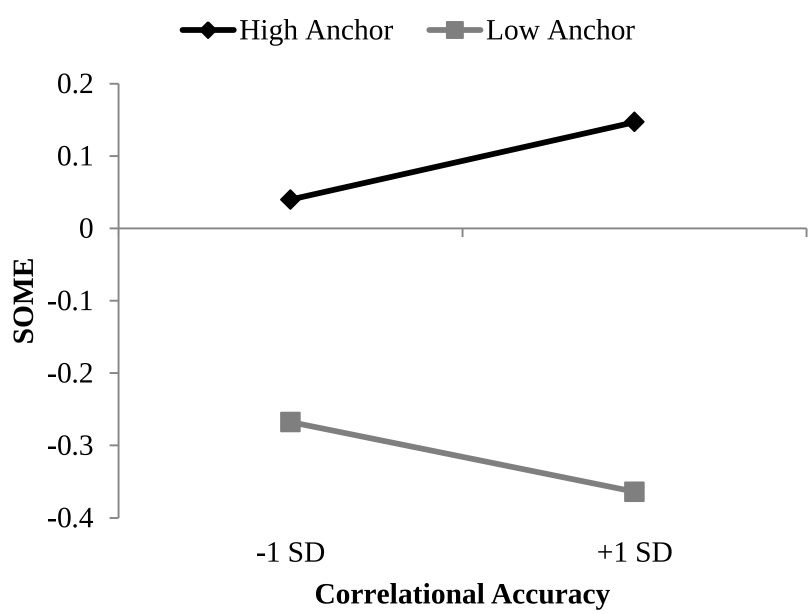

Figure 3.7 Relationship between correlational accuracy and SOME for the anchored estimates split by anchor condition.

Subjective Knowledge Measures and Anchoring Effects

Did participants' subjective knowledge judgments predict their susceptibility to anchoring effects and, if so, does this relationship depend on the type of knowledge the subjective measure was designed to assess (general knowledge, mapping knowledge, or metric knowledge)? If subjective knowledge did influence anchoring effects, one would expect an interaction between participants' anchor condition and their knowledge judgment. In other words, as subjective knowledge increased, the difference between high and low anchor estimates would get smaller.

I computed three separate regressions (one for each knowledge measure) using participants' anchor condition (high vs. low), their subjective knowledge judgments, and the interaction term to predict their average SOME value for the first 6 estimates. The interaction terms were not related to the participants' estimates when analyzing their general knowledge or mapping knowledge judgments ($ps > .35$). When examining participants' metric knowledge judgment, however, the interaction term marginally predicted participants' SOME values, $\beta = -.13$, $t(128) = 1.82$, $p = .07$. As can be seen in Figure 3.8, participants who reported high levels of metric knowledge were less influenced by anchors than participants who reported low levels of metric knowledge. This finding provided additional support for the idea that different types of knowledge differentially predict anchoring effects.

Discussion

The results of Study 3 are consistent with the prediction that increased metric knowledge—and not mapping knowledge—is associated with smaller anchoring effects. More generally, knowledge and anchoring effects are related, but the type of knowledge one has is an important moderator of this relationship.

An unexpected finding was that, when analyzing all 12 estimates (6 following a high anchor and 6 following a low anchor) and treating anchor as a within subjects factor, the rank-order knowledge condition showed substantially smaller anchoring effects than the no-knowledge condition. However, when analyzing only the first 6 estimates, the rank-order and no-knowledge conditions exhibited similar anchoring effects. While unexpected, in retrospect this pattern is sensible. Imagine a participant in the rank-order condition who first makes estimates following a high anchor. Because this person has very poor metric knowledge, the high anchors greatly influence his judgments and he greatly overestimates the country populations. For example, he might estimate the population of Senegal to be 50 million people after making a comparison with the high anchor (70 million). After making the first 6 estimates, this person would then make 6 more following low anchors. At this point, there are two factors that will influence this person's estimates—the anchors and this persons' rank-order knowledge. For example, if this person was then asked to estimate the population of Kenya after exposure to a low anchor (8 million), this person might remember that Kenya is more populated than Senegal. Therefore, he would provide an estimate above 50 million to be consistent with his previous estimate. In effect, his mapping knowledge helped him overcome the biasing influence of the small (8 million) anchor.

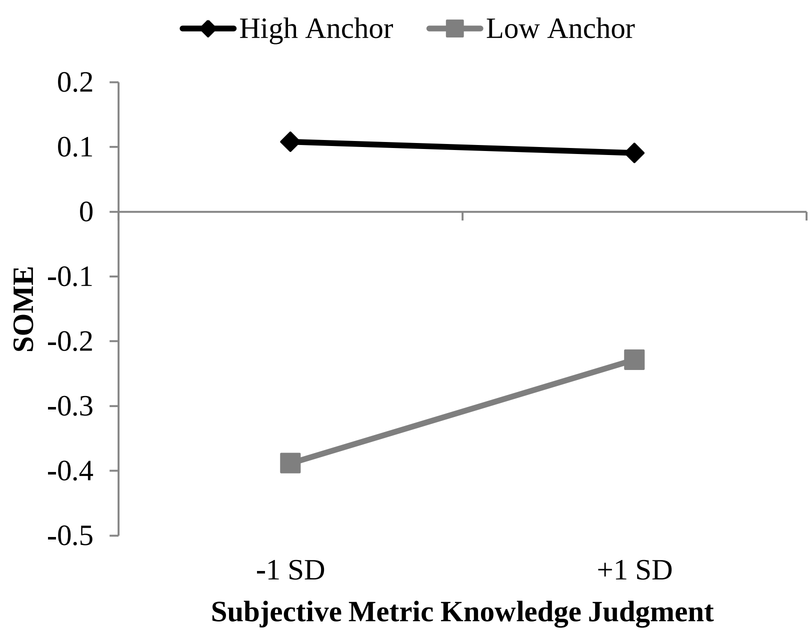

Figure 3.8 Relationship between the participants' subjective metric knowledge judgment and SOME for their anchored estimates.

The above conclusion is, of course, in contrast to the prediction that only metric knowledge is helpful in overcoming anchoring effects. It would appear that when making repeated estimates following both low and high anchors, any knowledge might be better than no knowledge. However, when making only a single estimate or if only exposed to a single anchor (i.e., high or low), metric knowledge decreases anchoring effects but mapping knowledge does not.

CHAPTER 4

MEASURING DIFFERENT TYPES OF KNOWLEDGE

Study 3 demonstrated that the type of knowledge one has is an important moderator of the relationship between knowledge level and anchoring effects. Study 4 used this finding and attempted to explain why previous investigations into the relationship between knowledge and anchoring effects have been inconsistent. Similar to most previous studies regarding the relationship between knowledge and anchoring, in Study 4 I measured (rather than manipulated) participants' knowledge and examined their anchoring effects. The expectation was that, when measuring knowledge correctly, increased knowledge level would be associated with decreased anchoring effects.

In addition to showing that manipulating different types of knowledge differentially impacts anchoring effects, Study 3 also provided support for the notion that measures of participants' metric and mapping knowledge differentially predict participants' susceptibility to anchors. As participants' metric accuracy decreased (as measured by the OME of their anchored estimates), they were more influenced by the anchors. Conversely, as mapping accuracy increased (as measured by correlational accuracy), they were more influenced by anchors. While this latter finding was unexpected, it is clear that metric and mapping accuracy differentially related to anchoring effects. A limitation of Study 3 with regards to the relationship between the measures of accuracy and anchoring effects is that they were assessed using the same estimates. In Study 4, I addressed this limitation by measuring participants' knowledge using a variety of tasks in one phase and then had them provide anchored estimates in a second phase.

It is possible that the moderating influence of knowledge will only be demonstrated at the extremes. In Study 1, for example, the difference in knowledge level between the full and no-knowledge conditions was quite substantial. Perhaps many previous investigations into the relationship between knowledge and anchoring demonstrated null results because the "naturally occurring" differences in knowledge between participants are not large enough to detect a difference. While this is possible, I expected that if the correct type of knowledge was measured, the predicted pattern will emerge.

Another goal of Study 4 was be to investigate the relationship between different types of knowledge. It is possible that, in most situations, participants' metric and mapping knowledge are highly correlated; participants who are high in metric knowledge are also high in mapping knowledge. If these two knowledge types are highly correlated, both types should similarly predict participants' estimates. While I did expect participants' levels of metric and mapping knowledge to be related, it was predicted that these types of knowledge would be distinct from one another and, therefore, differentially predict participants' estimates.

As I suggested earlier, there are numerous ways of measuring people's knowledge. The most widely used knowledge measure with respect to anchoring studies is to ask for a single or small number of general knowledge judgments (e.g., Critcher & Gilovich, 2007; Wilson et al., 1996). For example, in one study regarding estimates about the likelihood a linebacker will record a sack in an upcoming football game, the participants were asked to indicate their overall knowledge of football and report how frequently they watch football games (Critcher & Gilovich, 2007). While it is possible that subjective measures such as these will predict participants' anchoring effects (see e.g., Smith et al., 2011), it is likely that objective measures will outperform subjective measures. In order to compare the ability of objective and subjective measures, both types were assessed in this study.

Another possible knowledge measure would be to assess how much information a person has about a particular topic. In one study, for example, Wood (1982; see also Wood & Kellgren, 1988) asked participants to list as many brief statements about a particular topic as possible in a short amount of time. The researchers then counted the number of items listed as a measure of the amount of knowledge a person had about the topic. This measure might be useful in some situations (e.g., assessing the accessibility of information about a topic); however, it cannot account for the accuracy of the information which is perhaps a critical component to being able to overcome anchoring effects.

In the current study, knowledge was conceptualized as having accurate information about the topic. Therefore, I assessed knowledge using a number of tasks with objectively correct answers. My ultimate goal was to predict the participants' estimates about the population of U.S. states. Therefore, the primary knowledge measures concerned U.S. states specifically, rather than assessing people's general knowledge about populations. Presumably, specific measures will better predict later, similar judgments than more general measures (see Ajzen & Fishbein, 1977 for a related argument when prediction behavior from attitude measures).

In summary, Study 4 included both subjective and objective knowledge measures. The objective measures can further be split into measures designed to assess people's metric or mapping knowledge. The measures were then compared with regards to their ability to predict the participants' anchoring effects.

Method

Participants

One hundred seventeen participants from the U.S. were recruited to participants in the online survey using the MTurk web site. The participants were paid $0.25 each for their participation.

Materials

In Study 4, the goal was to use measures of participants' knowledge to predict their anchoring effects. Therefore, it was important that at least some of the participants were somewhat knowledgeable about the estimates they were making. In this Study, the participants made estimates about items they most likely had some knowledge of. Specifically, they estimated the populations of U.S. states (see Appendix E for a complete list of states used). In total, three lists of states were used. The first two lists (List A and List B) were used during the measurement phase and List C was used during the testing phase.

Procedure

After viewing the study information on MTurk, the participants were directed to the survey web site. After reading general instructions describing the survey, the participants started on the first of the two phases in this study. During the first phase—the measurement phase—the participants completed three tasks in a counterbalanced order. In the rank-order task, the participants rank-ordered a list of 6 states based on their populations. To do this, they were shown 6 states on the left side of the screen and they were asked to drag the states to an area on the right of the screen placing them in order from most to least populated. In the estimation task, they provided their estimates as to the exact populations of 6 states. They also provided an estimate as to the highest and lowest population values that seemed reasonable for each state. The lists of states that were used in these two tasks was counterbalanced across participants such that half of the participants rank-ordered List A and provided estimates of List B while the other half rank-ordered List B and provided estimates of List A.

In the third measurement task, the participants estimated the population of the average U.S. state, the population of the most populated state, and the population of the least populated state. The participants also provided subjective knowledge judgments as to their general knowledge of state populations, their knowledge of how the states compare to one another (i.e., their mapping knowledge), and their knowledge of the specific populations of states (i.e., their metric knowledge).

After the measurement phase, the participants proceeded to the second phase of the study—the testing phase. The participants were first given instructions about the testing phase and the arbitrary nature of the anchors. Next, they made estimates of 6 states in one of two predetermined orders. Half of the estimates were made after a comparison with a high anchor and half were made after a low anchor (the particular state estimates following high and low anchors were counterbalanced across participants). Unlike Studies 1 and 3, however, the order the participants received the anchors was not blocked. That is, the participants saw high and low anchors mixed together. The choice of anchor values also differed from the previous studies. In this study, the high anchors were roughly twice the actual population of the state and the low anchors were roughly half the population of the state. For example, the anchors used for Indiana that has a population of approximately 6.5 million were 13 and 3 for the high and low anchors, respectively. Finally, the participants were debriefed, thanked, and paid for their participation.

Results

Measures of Knowledge

No previous studies have examined how different measures of mapping knowledge, metric knowledge, and subjective knowledge estimates relate to each other. Therefore, Study 4 was somewhat exploratory in nature. As such, I calculated numerous measures of participants' knowledge and investigated how these related to one another and to the participants' anchoring effects.

Mapping Knowledge

I calculated two different measures of mapping knowledge. The first measure was calculated using the participants' responses to the rank-order task. To create this measure, each participant's ranking of the six states was correlated with the actual rankings. The average correlation for the rank task ($M = .55$, $SD = .33$) was significantly greater than zero, $t(107) = 17.23$, $p < .001$ (see Table 4.1 for a complete list of measures assessed). I submitted the r-to-z transformed values[2] to a 3 (measurement task order) X 2 (state list) ANOVA and this analysis revealed that the average correlations did not vary as a function of the measurement task order, $F(2, 102) = 0.44$, $p = .65$, $\eta_p^2 = .01$, the list the participants saw during the rank-order task, $F(1, 102) = 0.91$, $p = .34$, $\eta_p^2 = .01$, nor was there a significant interaction, $F(2, 102) = 0.16$, $p = .85$, $\eta_p^2 = .003$.

Table 4.1 Means, SDs, minimum, and maximum values of participants' measures of knowledge.

	Mapping Measures		Metric Measures			Subjective Judgments		
	Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
Mean (SD)	.55 (.33)	.55 (.30)	0.31 (0.19)	0.27 (0.24)	20.47 (14.64)	3.08 (1.43)	3.62 (1.35)	3.03 (1.49)
Min	-.60	-.41	.01	.01	.20	1	1	1
Max	1.00	1.00	0.89	0.95	93.20	7	7	7

Note. CA = Correlational accuracy.

2 Three participants had perfect rank-order correlations. Because an r-value of 1.0 cannot be Fisherized, an r-value of .99 was used, resulting in a transformed z-value of 2.65.

For the second measure of mapping knowledge, I used the participants' responses during the estimation task. Separately for each participant, I calculated a Spearman correlation between their population estimates and the actual state populations. The average correlation for the estimation task ($M = .55$, $SD = .30$) was significantly greater than zero, $t(114) = 19.57$, $p < .001$. I computed a 3 (measurement task order) X 2 (state list) ANOVA on the participants' r-to-z transformed values[3]. This analysis revealed a significant main effect of state list, $F(1, 109) = 7.06$, $p = .009$, $\eta_p^2 = .06$. Participants' correlational accuracy was higher when providing estimates of List B than List A. There was no effect of the order of the measurement task, $F(2, 109) = 0.01$, $p = .99$, $\eta_p^2 < .001$, nor an interaction, $F(2, 109) = 0.32$, $p = .72$, $\eta_p^2 = .006$.

For both measures, larger numbers represent greater accuracy (i.e., greater mapping knowledge). Given the relatively high correlations, it is clear that participants' mapping knowledge was fairly good. Also, it is interesting that correlational accuracy did not differ depending on whether the measure was obtained by having the participants rank-order a list of states or provide individual population estimates of the states.

Metric Knowledge

In addition to the two mapping knowledge measures, I created a number of measures of metric knowledge using the participants' population estimates in the estimation task and their responses to the average population, maximum population, and minimum population estimates. For the first measure, I calculated the average OME for the participants' 6 population estimates. Participants' average OME ($M = 0.31$, $SD = 0.19$) did not vary as a function of the measurement task order, $F(2, 111) = 0.57$, $p = .55$,

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[3] Four participants had perfect Spearman correlations, so r-values of .99 were converted to z-values.

η_p^2 = .01, or the list the participants saw during the estimation task, $F(1, 111) = 0.05$, p = .82, $\eta_p^2 < .001$.

I also calculated the OME of participants' judgment of the size of the average U.S. state. Based on an inspection of the participants' average estimates, it was clear that some people misunderstood the question. Therefore, the OME was only calculated if the participant's average estimate was greater than their estimate of the least populated state and less than their estimate of the most populated state. Estimates from 98 of the 117 (83.8%) participants satisfied this condition. The OME of participants' estimate of the average U.S. state ($M = 0.27$, $SD = 0.24$) did not vary across the three measurement task orders, $F(2, 95) = 1.87$, $p = .16$, $\eta_p^2 = .04$.

The final measure of participants' metric knowledge was calculated by first subtracting each participant's estimate of the least populated state from his or her estimate of the most populated state to generate their range. Then, I took the absolute value of the difference between participant's range and the actual range of state populations. This value ($M = 20.47$, $SD = 14.65$) did not vary as a function of the measurement task order, $F(2, 112) = 0.38$, $p = .68$, $\eta_p^2 = .007$. For all of the measures of metric knowledge, higher numbers are associated more error (i.e., high numbers indicate low metric knowledge).

Relationship Between Measures of Knowledge

Bivariate correlations between the different knowledge measures are presented in Table 4.2. There are a number of interesting relationships, but I will focus on some of the most important. Overall, it is apparent that each measure is more closely related to the other measures assessing the same knowledge type (mapping, metric, or subjective) as compared to the measures assessing different knowledge types. For example, the correlation between the two measures of mapping knowledge ($r = .35$) is, at least descriptively, greater than any other correlation with those two measures (largest other $|r|$

= .25). Similarly, the weakest correlation between the three metric knowledge measures (r = .42) is larger than the strongest correlation that they have with any other measure (|r| = .35). The three subjective measures are also more closely related to one another (smallest r = .77) than to the other measures (largest |r| = .35).

Table 4.2 Bivariate correlations between the different knowledge measures.

	Mapping Measures		Metric Measures			Subjective Judgments		
	Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
Rank task CA	-	.35***	-.17 a	-.22*	-.22*	.18 a	.08	.25*
Estimate task CA		-	-.24*	-.14	-.17 a	.16 a	.17 a	.09
OME			-	.60***	.53***	-.33***	-.34***	-.35***
OME of average state estimate				-	.42***	-.33**	-.33**	-.28**
Range error					-	-.28**	-.29**	-.34**
Overall Knowledge						-	.78**	.87**
Mapping Knowledge							-	.77**
Metric Knowledge								-

Note: CA = correlational accuracy; [a] $p < .10$, [*]$p < .05$, [**]$p < .01$, [***]$p < .001$

A second pattern worth noting is that the measures of different types of knowledge are sensibly related to each other. In general, smaller OME and range error (i.e., high metric knowledge) is associated with greater correlational accuracy (i.e., high mapping knowledge) and higher subjective knowledge judgments. It is also worth noting that participants' subjective judgments were related to their metric knowledge and not their mapping knowledge.

Relationship between Knowledge Measures and Accuracy of Anchored Estimates

Before examining the anchoring effects, I will describe how the knowledge measures assessed during the measurement phase were related to the correlational accuracy and OME of participants' estimates during the test phase—that is, the estimates given after comparisons with anchors. For correlational accuracy, I computed Spearman correlations for each participant between their estimates of the six states and the actual state populations (M = .35, SD = .34). For the mean-level accuracy, I computed the OME of participants' six population estimates (M = .22, SD = .11). These two measures were highly correlated, $r(117) = -.49$, $p < .001$, indicating that participants with higher correlational accuracy tended to have smaller OME values. This pattern is similar to the results found in the previous studies. Correlational accuracy and OME did not vary as a function of the particular states that were estimated after a high or low anchor or the order of the order the participants made their anchored estimates ($Fs < 1$, $ps > .45$, $\eta_p^2 < .01$).

Table 4.3 presents the correlations between the knowledge measures and the two forms of accuracy computed from participants' estimates during the test phase. As can be seen in the table, participants' accuracy of their test phase estimates was related to the knowledge measures derived from their estimates during the measurement phase. As would be expected, higher correlational accuracy, less error, and higher subjective knowledge judgments were associated with higher correlational accuracy and less error in the anchored estimates. In addition to the general pattern of correlations, it is worth noting that the measures of metric knowledge outperformed mapping knowledge measures when predicting the participants' OME and their correlational accuracy. This is somewhat surprising because one might expect the correlational accuracy of participants' anchored estimates to be correlated more highly with the mapping measures than the metric measures (and vice versa for the OME).

Table 4.3 Bivariate correlations between knowledge measures derived from measurement phase and accuracy of estimates given during the test phase (i.e., their anchored estimates).

	Mapping Measures		Metric Measures			Subjective Judgments		
	Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
CA (anchored estimates)	.21[*]	.25[**]	-.39[***]	-.25[*]	-.36[***]	.11	.18[a]	.17[a]
OME (anchored estimates)	-.16[a]	-.19[*]	.62[***]	.48[***]	.38[***]	-.27[**]	-.35[***]	-.27[**]

Note: CA = correlational accuracy; [a] $p < .10$, [*]$p < .05$, [**]$p < .01$, [***]$p < .001$

Anchoring effects and Knowledge Measures

As in the previous studies, I calculated the participants' average SOME separately for the population estimates following comparisons with high and low anchors (see Figure 4.1 for participants' raw estimates). Then, I computed the difference between these two values to create a measure of the participants' anchoring effect. Larger values for this anchoring index indicate a greater difference between high and low anchor estimates—that is, larger anchoring effects. Overall, there was a robust anchoring effect ($M = 0.19$, $SD = 0.17$), $t(116) = 12.42$, $p < .001$, $d = 2.31$. Participants' anchoring index did not vary as a function of the particular states that were estimated after a high or low anchor or the order the participants made their anchored estimates ($Fs < 1.3$, $ps > .26$, $\eta_p^2 < .02$).

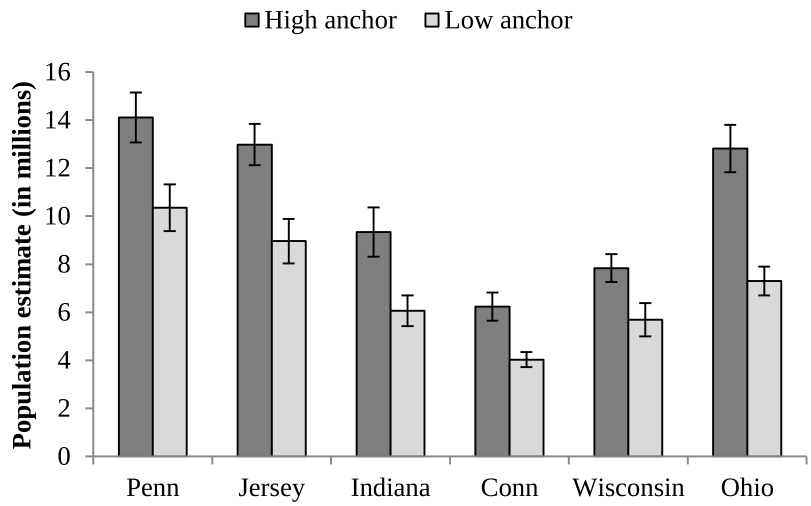

Figure 4.1 Average population estimates of each state based on anchor condition. Error bars represent ±1 SE.

The primary question of this study concerns how the anchoring index might be related to the different knowledge measures. To address this question, I computed bivariate correlations between the participants' knowledge measures and their anchoring index. In contrast to what was predicted, the measures of participants' knowledge were largely unrelated to their anchoring index (see Table 4.4). The correlations are in the predicted directions (i.e., higher correlational accuracy and subjective measures and smaller error measures were related to smaller anchoring effects). However, none of the correlations reach conventional levels of significance. Also, in contrast to what was predicted, the mapping measures outperformed the metric measures in their ability to predict the participants' anchoring effects—although the correlation was marginally significant for one measure and was not significant for the other.

Table 4.4 Bivariate correlations between knowledge measures and anchoring index.

	Mapping Measures		Metric Measures			Subjective Judgments		
	Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
Anchoring Index	-.16[a]	-.15	.07	.08	.08	-.02	-.07	-.10

Note: CA = correlational accuracy; [a] $p \leq .10$

Accuracy of Anchored Estimates and Anchoring Effects

In the previous studies, the correlational accuracy and OME of participants' anchored estimates were related to their anchoring effects. In this study, I also examined the relationship between the correlational accuracy and OME of participants' estimates given during the test phase and the anchoring effects of these same estimates. Bivariate correlations between the measures of accuracy, error, and anchoring effects revealed that correlational accuracy was significantly related, $r(117) = -.27$, $p = .003$, and OME was marginally related, $r(117) = .15$, $p = .10$, to participants' anchoring index. While the general pattern of results is consistent with what would be expected—greater correlational accuracy and less error was related to smaller anchoring effects—the strength of the associations is considerably weaker than in Studies 1 and 3. In Study 1, participants' correlational accuracy and OME were both highly correlated with their anchoring effects ($|r|s > .50$, $ps < .001$). In Study 3, participants' OME was strongly related to their anchored estimate, but their correlational accuracy was only very weakly related to their estimates. In the current study, correlational accuracy was more related to anchoring effects than was their OME. The weak relationships between accuracy/error of participants' anchored estimates and their anchoring effects was surprising. However, it might help shed light on why the knowledge measures may have failed to predict participants' anchoring effects.

The measures of mapping and metric knowledge derived from the correlational accuracy and OME during the measurement phase predicted participants' accuracy and error during the test phase. Specifically, participants who gave accurate estimates during the measurement phase tended to give accurate estimates during the test phase. The prediction of the current study was that, in addition to predicting accuracy/error in participants' anchored estimates, the measures of knowledge would also predict their anchoring effects. However, because the accuracy/error and anchoring effects were weakly related, perhaps it is not surprising that the measures of knowledge did not predict anchoring effects. An open question that warrants future research is why accuracy/error was only weakly related to bias (i.e., anchoring effects) in the current study, but strongly related in the previous studies.

Exploratory Analyses

The above analyses reveal that, for this study, a person's knowledge level strongly predicts the accuracy of his or her estimates during the test phase, but not his or her susceptibility to anchoring effects. This is, of course, in contrast to the previous studies where knowledge level predicted both the accuracy of people's estimates and their anchoring effects. I computed a number of additional analyses to help explore why the results of Study 4 differed from the previous studies. While the analyses reported below are interesting, they were exploratory and the conclusions from them should be considered with caution.

To help simplify the analyses, I computed indices of the participants' mapping, metric, subjective, and overall knowledge. To create the first three indices, I z-scored each of the knowledge measures and averaged the resulting values for each knowledge type. I also reverse coded the metric index so that higher values for each of the indices reflect greater knowledge. And finally, these three measures were averaged together to create an overall knowledge index (OKI) for each participant. As would be expected, higher OKI was associated with greater correlational accuracy and less error (OME) in the participants' anchored estimates (see Table 4.5). Higher OKI was also weakly related to the participants' anchoring index.

Table 4.5 Bivariate correlations between knowledge indices, the measures of accuracy, and anchoring index.

	Mapping Index	Metric Index	Subjective Index	Overall Knowledge Index
CA (anchored estimates)	.29**	.41***	.16^{a}	.39***
OME (anchored estimates)	-.22*	-.60***	-.32***	-.52***
Anchoring Index	-.18*	-.13	-.07	-.17^{a}
Overall Knowledge Index	.65***	.76***	.76***	-

Note: CA = correlational accuracy; ^{a} $p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

For all knowledge indices, higher numbers represent greater knowledge.

For the remainder of the analyses, I created high and low knowledge groups based on a median split of participants' OKI. The high and low OKI groups did not differ in their anchoring index, $t(115) = 0.23$, $p = .82$. They did, of course, differ in terms of the correlational accuracy and OME of their estimates given during the test phase (both ts > 3.2, ps < .01). Similar to the results presented earlier, the high OKI group gave anchored estimates that were more accurate and exhibited less error than the low OKI participants, but they exhibited similar anchoring effects. This, again, highlights the disassociation between accuracy and bias.

Separate analyses on the high and low OKI groups reveal a number of fairly dramatic differences. Table 4.6 presents the bivariate correlations between the accuracy/error measures of their anchored estimates and participants' anchoring effects. An inspection of these correlations reveals that, for the low OKI participants, the accuracy/error of their anchored estimates is unrelated to their anchoring index. In contrast, for the high OKI participants, the accuracy/error of their anchored estimates is strongly related to their anchoring index.

Table 4.6 Bivariate correlations between accuracy of anchored estimates and anchoring index split for low and high OKI participants.

		CA (anchored estimates)	OME (anchored Estimates)
Low OKI	OME (anchored estimates)	$-.31^{*}$	-
	Anchoring Index	-.12	-.01
High OKI	OME (anchored estimates)	$-.58^{***}$	-
	Anchoring Index	$-.43^{**}$	$.40^{**}$

Note: CA = correlational accuracy; OKI = Overall Knowledge Index; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

The difference between the high and low OKI participants is also revealed when examining the correlations between the knowledge indices, accuracy of anchored estimates, and anchoring index (see Table 4.7). For the low OKI participants, the three knowledge indices were weakly related to the participants' accuracy; the only significant relationship was between participants' metric index and their OME. Also, none of the knowledge indices were related to the participants' anchoring index. The results were quite different for the high OKI participants. The participants' mapping and metric indices were sensibly related to the accuracy of their estimates. Furthermore, these two knowledge indices were significantly correlated with the participants' anchoring effects. Taken together, these findings suggest that knowledge level is predictive of anchoring effect, but only participants who have some knowledge of the topic area (i.e., the high OKI participants).

Table 4.7 Bivariate correlations between knowledge indices, the measures of accuracy, and anchoring index for high and low OKI participants.

		Mapping Index	Metric Index	Subjective Index	Overall Knowledge Index
Low OKI	CA (anchored estimates)	-.03	.22^{a}	-.05	.14
	OME (anchored estimates)	.11	-.47***	-.15	-.45***
	Anchoring Index	-.02	-.04	-.08	-.10
High OKI	CA (anchored estimates)	.30*	.48***	-.03	.35**
	OME (anchored estimates)	-.27*	-.63***	-.10	-.45***
	Anchoring Index	-.34**	-.36**	-.06	-.38**

Note: CA = correlational accuracy; OKI = Overall Knowledge Index; ^{a} $p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

For all knowledge indices, higher numbers represent greater knowledge.

Examining the correlations between the knowledge indices and anchoring index provides support for the notion that knowledge level influences anchoring effects—although this relationship is more complex than predicted. An important question that remains is which knowledge index best predicts the participants' anchoring effects. To address this question, I ran separate regression analyses for the high and low OKI groups predicting the participants' anchoring index from their three knowledge indices. For the low OKI group, none of the knowledge indices predicted their anchoring index ($ps > .45$). For the high OKI group, the metric index significantly predicted participants' anchoring index, $\beta = -.27$, $t(55) = 1.97$, $p = .05$. The participants' mapping index marginally predicted their anchoring index, $\beta = -.24$, $t(55) = 1.78$, $p = .08$. These results suggest that, for relatively high knowledge people, higher levels of metric or mapping knowledge are associated with lower anchoring effects. This is somewhat unexpected because it was predicted that, when controlling for the other measures, only metric knowledge would be associated with anchoring effects. However, given that this pattern only emerged for half of the participants, conclusions draw from these analyses are fairly tenuous.

The above analyses focused on how the knowledge indices were related to participants anchoring index. It is also instructive to look at the relationship between anchoring effects and the individual measures. As can be seen in Table 4.8, the knowledge measures were largely uncorrelated with the low OKI participants' anchoring index. However, a number of the metric and mapping measures were correlated with anchoring effects for the high OKI participants. Again, this suggests that the knowledge measures can predict anchoring effects, but only for those participants who are somewhat knowledgeable about the topic. In addition to the bivariate correlations, I also conducted separate regression analyses for the high and low OKI participants predicting their anchoring index from the "best" mapping, metric, and subjective measure. For the low OKI participants, the best measures were the rank task CA, range error, and subjective metric knowledge judgment. For the high OKI participants, the best measures were the estimate task CA, range error, and subjective mapping knowledge judgment. For the low OKI participants, their rank task CA significantly predicted their anchoring index, $\beta = -.28$, $t(50) = 2.05$, $p = .05$, and their subjective metric knowledge judgment marginally predicted their anchoring index, $\beta = -.25$, $t(55) = 1.81$, $p = .08$. For the high OKI participants, only the range error predicted their anchoring index, $\beta = .32$, $t(54) = 2.41$, $p = .02$. The best mapping and subjective measures did not predict the high knowledge participants' anchoring effects (ps > .21). In other words, even when controlling for the other measures, the metric measure significantly predicted participants' anchoring effect.

Table 4.8 Bivariate correlations between knowledge measures and anchoring index for high and low OKI participants.

		Mapping Measures		Metric Measures			Subjective Judgments		
		Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
Anchoring Index	Low OKI	-.12	.02	.02	-.003	-.07	.02	-.05	-.18
	High OKI	-.25[a]	-.31*	.21	.30*	.38**	-.03	-.10	-.04

Note: CA = correlational accuracy; OKI = Overall Knowledge Index; [a] $p < .10$, * $p < .05$, ** $p < .01$

Non-linear Analyses

One possibility that has not yet been discussed is that the relationship between the knowledge measures and anchoring index is non-linear. Thus far, the analyses would only detect a linear relationship. Tables 4.9 and 4.10 present the R^2 values for the linear and non-linear relationships between the participants anchoring index and their knowledge measures and knowledge indices. An inspection of these tables reveals that, while some non-linear models better account for the results, none of the models do particularly well.

Table 4.9 R^2 values for linear and non-linear relationships between knowledge measures and anchoring index.

		Mapping Measures		Metric Measures			Subjective Judgments		
		Rank task CA	Estimate task CA	OME	OME of average state estimate	Range error	Overall Knowledge	Mapping Knowledge	Metric Knowledge
Anchoring Index	Linear R^2	.025[a]	.023	.005	.007	.006	.000	.005	.010
	Quadratic R^2	.027	.058[*]	.007	.047[a]	.048[a]	.004	.005	.011
	Cubic R^2	.030	.063[a]	.061[a]	.049	.040[a]	.014	.005	.024

Note: CA = correlational accuracy; [a] $p < .10$, [*] $p < .05$

Table 4.10 R^2 values for linear and non-linear relationships between knowledge indices and anchoring index.

		Mapping Index	Metric Index	Subjective Index	Overall Knowledge Index
Anchoring Index	Linear R^2	.033[*]	.017	.005	.030[a]
	Quadratic R^2	.033	.037	.005	.058[*]
	Cubic R^2	.034	.038	.005	.058[a]

Note: [a] $p < .10$, [*] $p < .05$

Another way of visualizing the complex relationship between knowledge and anchoring is displayed in Figure 4.2. The best fitting model for the relationship between participants' overall knowledge index and their anchoring index is a quadratic model (represented by the thin black line in Figure 4.2). This model accounts for approximately 6% of the variance. When examined separately, the best fitting line for the low OKI participants is cubic (the bolded dark line) while for the high OKI participants, a linear model performs the best (the bolded light line) with these models accounting for approximately 13% and 14% of the variance, respectively. This pattern is, of course, quite complex. However, it is clear that it is not best represented as a "simple" non-linear relationship.

Discussion

In Study 4, numerous analyses were conducted, so I will describe the most important. First, as would be expected, the measures of participants' knowledge during the measurement phase predicted the accuracy of their anchored estimates given during the test phase. Second, in contrast to the previous studies, the accuracy of the anchored estimates was not strongly related to participants' anchoring effects. And finally, the prediction that measures of metric knowledge—and not the other knowledge measures—would be related to participants' anchoring index was not supported. If anything, the mapping knowledge measures were better associated with anchoring effects, although the relationships were quite weak and generally not significant (see Table 4.4).

Why did Study 4 fail to find the expected relationship between anchoring and knowledge? It is, of course, possible that there is no relationship between anchoring and knowledge level. This seems quite unlikely given the results of Studies 1, 2, and 3, as well as other research I have conducted (see e.g., Smith et al., 2011). Another possible reason is that very few of the participants were knowledgeable about the topic area. It could have been the case that I was essentially comparing anchoring effects of very-low-knowledge people to the anchoring effects of somewhat-low-knowledge people.

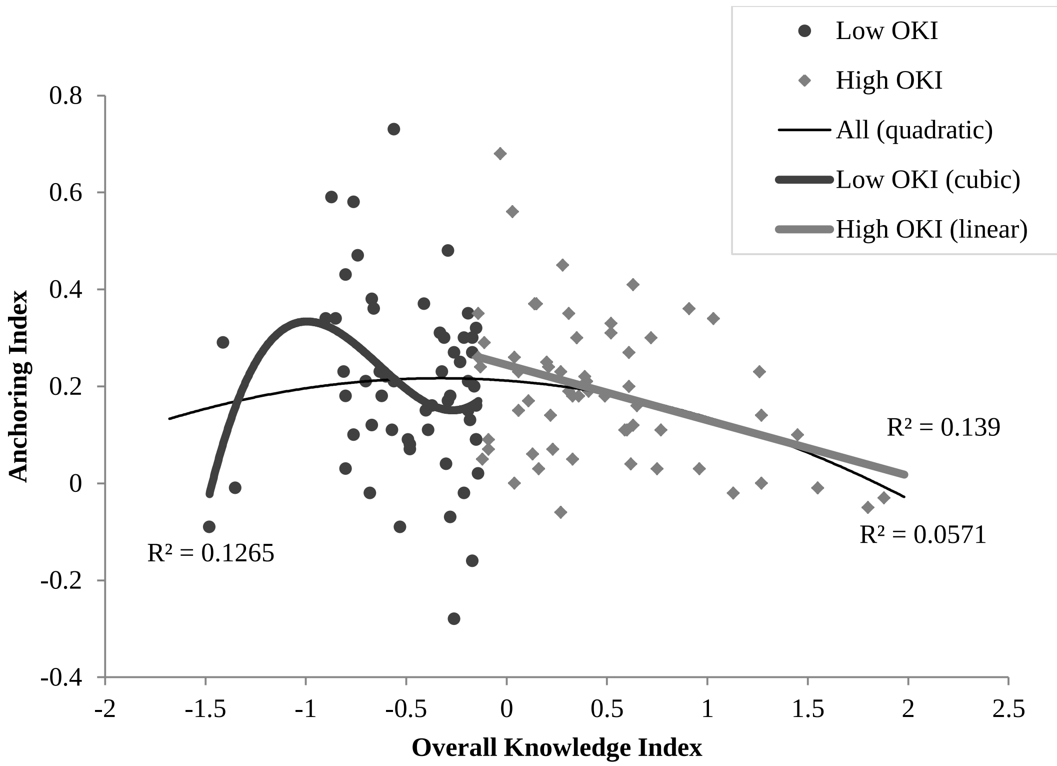

Figure 4.2 Scatterplot of overall knowledge index and anchoring index.

There is also another reason why the results of Study 4 might not have turned out as predicted. Based on the results of the previous studies, I assumed that increased error would be associated with increased anchoring effects. That is, deviation of the estimate from the actual value (error) will be positively correlated with systematic deviation of the estimate from the actual value in the direction of the anchor (bias). However, the relationship between error and bias is probably not as simple as I anticipated. Highly knowledgeable people will most likely give estimates that are low in error and bias. People who are extremely low in knowledge will certainly give estimates that have greater error. However, if the estimates from low knowledge people are essentially random guesses, the amount of bias (i.e., systematic deviation in the direction of the anchor) in their estimates could be low, high, or anywhere in between.

If this is true, it seems likely that the relationship between accuracy/error and bias will be stronger for high knowledge participants than for low knowledge participants. I already presented results from Study 4 that are consistent with this idea (see Table 4.6). Additionally, I examined the relationships between accuracy and bias in Study 1 split by the knowledge conditions. As can be seen in Table 4.11 below, the correlational accuracy and OME of participants' anchored estimates were highly correlated with anchoring effects for the full knowledge participants. In contrast, the correlations were much weaker for the no knowledge participants. Therefore, it could be the case that the experimental manipulations of knowledge were strong enough to overcome the differing relationships between accuracy and bias. In the current study, however, the smaller differences in knowledge did not have the same impact.

Table 4.11 Bivariate correlations between accuracy of anchored estimates and anchoring index split for full and no-knowledge participants in Study 1.

		CA (anchored estimates)	OME (anchored Estimates)
No Knowledge	OME (anchored estimates)	-.31	-
	Anchoring Index	-.38[a]	-.17
Full Knowledge	OME (anchored estimates)	$-.41^{*}$	-
	Anchoring Index	$-.53^{**}$	$.54^{**}$

Note: CA = correlational accuracy; $^{*}p < .05$, $^{**}p < .01$

A final reason as to why the results of Study 4 did not turn out as predicted might have to do with how knowledge was operationalized. I measured knowledge by assessing the accuracy of the information people had about the topic. However, another method could have been used. Rather than focusing on the accuracy of a person's knowledge, assessing the certainty people have in their own knowledge might be useful. For example, imagine a person who thinks the population of Ohio is 30 million and she is very sure of this value. Even though her knowledge is not at all accurate (the actual population of Ohio is approximately 11.5 million), she would likely exhibit small anchoring effects because of her certainty in her knowledge. On the other hand, imagine a person who thinks the population of Ohio is 11 million people, but he is unsure if this is the correct value. Even though he has accurate knowledge, he might show very robust anchoring effects because of his uncertainty. Therefore, it might not be the accuracy of one's knowledge that moderates anchoring effects, but the certainty that one has in their knowledge.

I should note that, while the above argument does suggest that knowledge could be operationalized in a different way, understanding the different types of knowledge is still quite important. That is, certainty in one's metric knowledge might be associated with decreased anchoring effects while certainty in one's mapping knowledge might not. For example, if a person is very certain that the population of Ohio is more than the population of Illinois, he still might show large anchoring effects because his mapping knowledge will not help to overcome the biasing influence of anchors.

It is also worth noting that the certainty someone has in his or her knowledge is not the same thing as the confidence a person might have in his or her estimate. Therefore, I would not necessarily expect that people who are highly confident in their estimate to show small anchoring effects. There are a variety of reasons a person might have confidence in his or her estimate—some of which might be unrelated to their susceptibility to anchoring effects (see the section titled "Knowledge, Confidence, and

Anchoring Effects" in Chapter 5 for further discussion of the role of confidence in one's estimate).

Final Points

While the results of Study 4 did not turn out as predicted, there are a few interesting points worth discussing. First, the knowledge measures were better correlated with measures within a knowledge type than across the knowledge types. This provided further evidence that these knowledge types are distinguishable. Second, the objective knowledge measures outperformed the subjective measures when predicting participants' accuracy/error and, to a much lesser extent, their anchoring effects. And finally, this study highlights the complex relationship between knowledge and anchoring effects. Knowledge level was certainly an important factor to consider (e.g., see Table 4.9), even though the exact relationship between the knowledge measures and anchoring effects was unclear.

CHAPTER 5

SUMMARY, IMPLICATIONS, AND FUTURE RESEARCH

The results of Studies 1, 2, and 3 clearly indicated that knowledge level is an important consideration when examining anchoring effects. In Study 1, those participants who studied a list of country populations—i.e., the full-knowledge participants—were less influenced by anchors than participants who learned irrelevant information. Importantly, the full-knowledge participants showed smaller anchoring effects when making estimates about countries they previously studied and about new countries. In Study 2, those participants who studied a list of new car prices were less influenced by anchors when estimating the average price of a new car than participants who learned irrelevant information. However, a decrease in anchoring effects only occurred for the participants learning the information about new car prices when the instructions encouraged them to carefully process the information. Taken together, these studies demonstrated that increased knowledge leads to decreased anchoring effects when making estimates about specific items or the average of multiple items, and across different topic domains. These studies also revealed why a previous study failed to find a relationship between knowledge level and anchoring effects. Specifically, because anchoring effects are so strong, it is important that the participants carefully process the information in the learning phase in order to overcome the biasing influence of the anchors.

Study 3 demonstrated that the type of knowledge one has is a critical moderator of the relationship between knowledge level and anchoring effects. In this study, participants learned information designed to influence their metric or mapping knowledge. In the distribution knowledge condition, for example, the participants saw a number of country populations without any country names associated with the population values. Therefore, these participants learned the range and distribution of country populations (i.e., metric information), but did not get any information about how specific countries relate to one another (i.e., mapping knowledge). In the rank-order knowledge condition, the participants were shown a list of country populations ordered from most to least populated. Therefore, they learned how the countries related to one another, but not the actual populations of these countries.

The results of Study 3 supported the prediction that only those participants in conditions that increased metric knowledge would exhibit reduced anchoring effects. Conditions that manipulated mapping knowledge showed anchoring effects that were similar to the no-knowledge condition. Because previous investigations into the relationship between knowledge and anchoring have not made a distinction between different types of knowledge, it is not surprising that the findings from these studies are quite mixed. The results of this study highlight the importance of not only considering knowledge level, but also the type of knowledge one has.

In Study 4, I measured the participants' metric, mapping, and subjective knowledge in the first phase of the study. Then, the participants estimated the population of a number of U.S. states after comparisons with high and low anchors. In contrast to my prediction, none of the knowledge measures significantly predicted the magnitude of the participants' anchoring effects. The exploratory analyses, however, revealed that the metric and mapping knowledge measures significantly predicted the high knowledge participants' anchoring effects. These same measures did not predict the anchoring effects of the low knowledge participants. While this pattern was unexpected, it does highlight the importance of considering the participants' knowledge when studying anchoring effects.

Even though the results of Study 4 did not turn out as expected, given the results of Studies 1, 2, and 3, I feel it is safe to conclude that high knowledge participants are less influenced by comparisons with anchors than low knowledge participants. Furthermore, not all types of knowledge have the same impact on anchoring effects.

Increases in metric knowledge—and not mapping knowledge—produced decreased anchoring effects. Finally, the success of the first three studies indicates that taking the participants' knowledge level into account can be important when conducting research into the influence of anchors.

The Importance of Considering Knowledge Level

Knowing that knowledge level moderates anchoring effects is important because it might provide some insights into other apparent discrepancies in anchoring research. For example, the research is mixed as to whether the extremity of an anchor influences the magnitude of the anchoring effect (e.g., Chapman & Bornstein, 1996; Marti & Wissler, 2000; Mussweiler & Strack, 2000; Strack & Mussweiler, 1997). Some studies have found that extreme anchors produce significantly larger anchoring effects than moderate anchors whereas others have found that extreme and moderate anchors produce similar anchoring effects. When investigating the influence of anchor extremity, it might be important to take the participants' knowledge level into account. Specifically, it is possible that knowledgeable participants will be less influenced by extreme anchor while low-knowledge participants will be more influenced by extreme anchors. High knowledge participants might be able to immediately reject extreme anchors, thereby reducing their impact. Low knowledge participants, on the other hand, will have to consider an extreme anchor as a possible answer resulting in a large anchoring effect.

Imagine, for example, a study where a variety of anchor values are used that differ in their extremity. Given the above reasoning, I would expect that the difference between an estimate given by a high knowledge and low knowledge participant would increase as the anchor gets more extreme. Figure 5.1 plots hypothesized estimates from high knowledge (the solid black line) and low knowledge (the dashed gray line) participants after a comparison with a high (right side of the figure) or low anchor (left side of the figure). Notice that as the high anchor gets higher and the low anchor gets lower, the difference between high and low knowledge participants increases. Also note the decreasing slope of both lines. This reflects the assumption that, for example, a high anchor of 100 million might produce a larger anchoring effect than a more moderate anchor (e.g., 20 million) when estimating the population of Ohio. However, 100 million will produce a similar anchoring effect as compared to 300 million. As shown in the figure below, high knowledge participants would be expected to reach the plateau earlier than low knowledge participants.

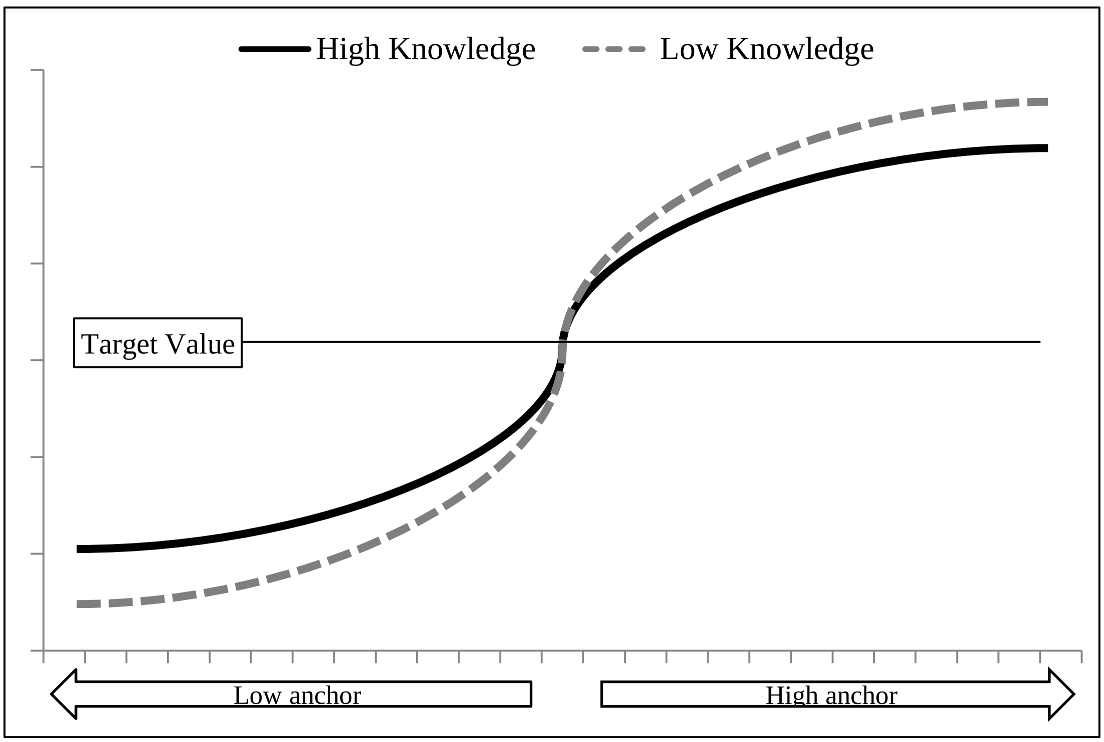

Figure 5.1 Hypothesized relationship between anchor extremity and knowledge level.

Interestingly, the hypothesized pattern of results described above can potentially account for some of the discrepant findings regarding the relationship between knowledge and anchoring effects. Namely, if a study used moderate anchors, the difference between anchoring effects for high and low knowledge participants might be quite small or even nonexistent. On the other hand, if extreme anchors are used, the difference between anchoring effects of high and low knowledge participants might be quite pronounced. In fact, two of the most widely cited anchoring studies that show no difference between high and low knowledge participants used moderate anchors (Englich et al., 2006; Northcraft & Neale, 1987). Northcraft and Neale (1987) had realtors and university students estimate the price of a house after comparisons with anchors. The house had been appraised at $135,000 and the anchors that were used were $119,900, $129,900, $139,900, and $149,900. As expected, the estimates following the low anchors were lower than the estimates following the high anchors. Also, the magnitude of the anchoring effect did not differ substantially for experts and novices. However, it seems possible that the difference between experts and novices would have been evident if more extreme anchors were used (e.g., $89,900 and $179,900).

Similarly, Englich et al. (2006) had legal experts and non-experts read a hypothetical scenario about a woman convicted of shoplifting. The experts gave recommendations about the length of probation the woman should receive after considering a high (9 months) or low (3 months) anchor. The participants gave higher estimates after considering a high anchor than a low anchor. Again, the magnitude of the anchoring effect was similar for experts and non-experts. However, if the high anchor was 36 months, there might have been a different conclusion. The experts may have rejected this value as clearly too high and given a response of 10 months. The non-experts, on the other hand, might not know what constitutes an appropriate probation length and, therefore, give an estimate of 20 months.

The idea that the difference between anchoring effects of high and low knowledge participants will be minimal when using moderate anchors can also account for the null results found in Study 4. The anchors used in Study 4 were approximately double and half (high and low, respectively) of the actual population of each state. Given that people generally have fairly poor knowledge of populations, these anchor values might not have been particularly extreme. Therefore, it is possible that the metric and mapping knowledge measures would have better predicted anchoring effects if I had used more extreme anchors.

In addition to helping to clarify the impact of anchoring extremity on anchoring effects, considering participants' knowledge level might also shed light on other possible moderators of anchoring effects. Numerous studies have investigated whether anchoring effects are increased when people have limited cognitive resources or mitigated when people are highly motivated. The findings suggest that anchoring effects are immune to factors that limit participants' cognitive resources, such as time limits (Mussweiler & Strack, 1999) and cognitive load (Epley & Gilovich, 2006). Additionally, anchoring effects are not influenced by increasing participants' motivation through incentives for accuracy (Tversky & Kahneman, 1974; Wilson et al., 1996; but see Simmons et al., 2010). The failure of manipulations of effortful processing to influence anchoring effects has led researchers to abandon the anchoring and insufficient adjustment account because it relies on an effortful adjust process—something that should be influenced by manipulating effortful processing. However, it is possible that the influence of factors like cognitive load and incentives for accuracy are moderated by knowledge level.

Smith, Windschitl, and Bruchmann (2009) conducted a study to test the idea that knowledge level is an important consideration in understanding the impact of cognitive load on anchoring effects. In this study, participants answered a number of football related questions (e.g., "How many total points did the Chicago Bears score in all games during the past season?"). There were three factors in this study—two manipulated and one measured. First, the anchor value was manipulated such that the participants answered the football questions after comparisons with high or low anchors. Second, half of the participants answered the questions while under cognitive load while the other half were not under load. And finally, the participants provided subjective measures of football knowledge and completed a football knowledge quiz. These were combined to create an overall measure of the participants' football knowledge.

The results of the study revealed that, for the low knowledge participants, the cognitive load manipulation did not influence the magnitude of their anchoring effect. In contrast, for the high knowledge participants, the participants who were under cognitive load exhibited larger anchoring effects than those participants who were not under cognitive load. Presumably, limiting the participants' ability to recruit background information to inform their estimates was only impactful if the participants had information to recruit (i.e., they were relatively knowledgeable about football).

In addition to influencing anchoring effects, it is also possible that knowledge level will moderate the *consequences* of anchoring effects. To understand why this might be the case, recall that there are currently three general accounts that have been described to explain anchoring effects. Two of these accounts (selective accessibility and anchoring and insufficient adjustment) rely on either the activation or recruitment of knowledge about the target item. For example, considering an anchor might increase the activation of anchor consistent information (Mussweiler & Strack, 1999). Or, the anchor might serve as a starting point and people might effortfully adjust away from the anchor value (Tversky & Kahneman, 1974). Presumably, this adjustment process only occurs when people know which way to adjust and are motivated to recruit additional information (Simmons et al., 2010). The third account—numeric or magnitude priming—does not rely on the activation of information about the target item, but simply suggests that the anchors increase the activation of numbers or magnitudes that are similar to the anchor value. Given that two accounts require that people have information about the target item and one does not, it seems possible that the mechanism producing anchoring effects might differ depending on the amount of knowledge one has about the target item. If the anchoring effects are caused by different mechanisms, this might lead to differing consequences of exposure to anchors (Blankenship et al., 2008).

Imagine that people are asked to estimate the length of the Mississippi River after a comparison with a high anchor (e.g., 5000 miles). It is possible that a highly knowledgeable person might recruit a large amount of (biased) information that is consistent with the Mississippi River being quite long (e.g., "The Mississippi River crosses virtually the entire U.S. from north to south."). On the other hand, a low knowledge person—perhaps someone not from the U.S.—might not have any relevant information about the Mississippi River. Therefore, it is unlikely that any resulting anchoring effects could be caused by an increase in the accessibly of anchor consistent information. Most likely, the anchoring effects of the low knowledge person would be caused by priming or because the anchor is perceived to be a reasonable guess (Schwarz, 1994).

The above example describes a situation where anchoring effects in high knowledge people are caused by relatively thoughtful processes while anchoring effects in low knowledge people are caused by non-thoughtful processes. Theories of attitudes and persuasion suggest that attitudes that result from thoughtful vs. non-thoughtful processes might have different consequences (Petty & Cacioppo, 1986). For example, attitudes that were derived through thoughtful processes should last longer and be more resistant to counter-attitudinal information. Recently, Blankenship et al. (2008) tested this prediction with regards to anchoring effects. They found that anchored estimates given while under or not under cognitive load were equally influenced by anchors, but those estimates given while not under load were more resistant to change. Presumably, the estimates given while under load were produced by relatively non-thoughtful processes while those given while not under load were produced by thoughtful processes (see also, Wegner et al., 2011).

The above findings suggest that while both high and low knowledge people might be biased by anchors, the estimates given by high knowledge people would persist longer and be more resistant to change than estimates given by low knowledge people. In other words, it is possible that knowledge level might moderate the consequences of anchoring effects. However, in contrast to the moderating role of knowledge level and anchoring effects, high knowledge people would be more likely to show lasting consequences of anchoring than low knowledge people.

Knowledge, Confidence, and Anchoring Effects

In Studies 1, 2, and 3, the amount of information people had about a topic area was manipulated and I examined their anchoring effects. It is likely that giving people additional information during the learning phase also increased their confidence in their ability to give accurate estimates. Previous research has found that the more information a person can recruit is associated with greater confidence in their judgments (e.g., Arkes, Dawes, & Christensen, 1986; Stewart, Heideman, Moninger, & Reagan-Cirincione, 1992; Tramfimow & Sniezek, 1994). Interestingly, recruiting more information does not always lead to more accurate judgments (Gill, Swann, & Silvera, 1998; Hall, Ariss, & Todorov, 2007). This is especially true when additional information leads people to rely on biased or non-diagnostic cues. For example, Hall et al. (2007) had participants predict the outcome of basketball games. All participants were presented with statistical information about both teams (e.g., their overall record). Half of the participants were told the names of the teams competing while the other half were not. Those participants who received the names of the teams were more confident in their prediction, were willing to bet more on the outcome of the game, and felt that receiving the team names was valuable information that improved their prediction. In reality, those participants who did not receive the team names made more accurate predictions. This occurred because receiving the team names caused people to ignore the diagnostic statistical information and rely on other cues (e.g., the familiarity of the teams competing). In sum, more information led to greater confidence, but worse accuracy.

With regards to the studies described in this dissertation, it seems likely that those participants who received information before making their estimates were more confident than those participants who did not receive information. However, not all information led to decreased anchoring effects. Therefore, the increase in confidence was only associated with decreased anchoring effects when the participants received metric information. The participants who received mapping information before making their estimates might have been just as confident as the participants who received matric information, but they showed significantly larger anchoring effects. If this was the case, it would highlight the fact that greater confidence is often not associated with a diminished susceptibility to biased responding (e.g., Gill et al., 1998; Hall et al., 2007). At this point, the relationships between knowledge level, confidence, and anchoring effects are purely speculation. Future studies could measure participants' confidence in addition to manipulating knowledge level to examine how they relate to anchoring effects.

Knowledge and Different Types of Anchoring

The studies described in this dissertation were designed to test the effects of knowledge level on anchoring effects from externally provided anchors. There are, however, other types of anchoring effects—incidental anchoring, for example. While the results of the current studies do not speak directly to how knowledge might moderate anchoring effects from incidentally presented anchors, it is worth examining previous research in light of the results of the current studies. The research investigating knowledge and incidental anchoring (sometimes referred to as basic anchoring) appears to be mixed. For example, Wilson et al. (1996) found that knowledge level moderated anchoring effects while Critcher and Gilovich (2007) found that knowledge did not moderate anchoring effects. It should be pointed out, however, that the measures of knowledge used in these two studies were quite different from one another. Wilson et al.

(1996; Study 1) had participants make estimates about the number of countries in the United Nations and assessed their knowledge by asking how knowledgeable they were about the number of countries in the United Nations. Critcher and Gilovich (2007, Study 1) had participants estimate the likelihood that a particular football player would register a sack in an upcoming game. Knowledge was measured in this study by asking participants how knowledgeable they were about football, in general. Wilson et al.'s knowledge measure was certainly more specific and, perhaps, more relevant when predicting the participants' estimates. Beyond that, Wilson et al.'s measure most likely tapped into the participants' metric knowledge about the target estimate (e.g., plausible range of responses for the number of countries in the UN) while Critcher and Gilovich's (2007) measure did not specifically address participants' metric knowledge. In fact, a person indicating he or she has high football knowledge might not know anything about the target estimate (i.e., the likelihood of registering a sack in a football game). Given the discrepancy in the knowledge measures, it is perhaps not surprising that the patters of results differed across these two studies. Future research could investigate the relationship between knowledge and anchor effects from incidentally presented anchor. Namely, different types of knowledge could be manipulated to examine whether high knowledge participants show smaller incidental anchoring effects than low knowledge participants and whether the decrease in bias is caused by an increase in metric knowledge.

Knowledge Level and Other Biases

In addition to informing how knowledge might relate to other types of anchoring effects, the current studies also shed light on the relationship between knowledge and other biases. For example, in a paradigm used to investigate the hindsight bias, participants first make estimates about numerous targets (e.g., the populations of countries). During a later session, the participants are told the actual answers and are then asked to recall their original estimates. In general, participants' recalled estimates are closer to the actual answer than their original estimate (Hawkins & Hastie, 1990). Similar results are found when, instead of being provided with the actual answer prior to the recall task, participants are given the estimate of a co-participant (Pohl, 1998a) or even a randomly generated number (Pohl, 1998b).

Like the research into anchoring effects, research looking at the relationship between knowledge and the hindsight bias is quite mixed. In fact, two meta-analyses of hindsight bias studies have been conducted and one found that greater knowledge led to smaller effects (Christensen-Szalanski & Willham, 1991) while the other found no such relationship (Guilbault, Bryant, Brockway, & Posavac, 2004). The studies investigating this relationship made no distinction between different types of knowledge. Therefore, it would be useful to examine how different types of knowledge predict a participant's susceptibility to the hindsight bias. Presumably, if people have the correct type of knowledge, greater knowledge would lead to a smaller hindsight bias.

Theoretical Implications

As described in the Introduction, the accounts of anchoring effects are largely silent on the impact of knowledge level. However, given the growing body of research that implicates knowledge level as a critical determinant of the magnitude of anchoring effects, it is important to specify how knowledge level can fit within an account. The finding that knowledge moderates anchoring effects can best be incorporated into the anchoring and insufficient adjustment account. As a reminder, this account suggests that people use the anchor value as a starting point and then adjust away from the anchor value to provide their estimate (Epley & Gilovich, 2001; Tversky & Kahneman, 1974). Presumably people must recruit information to guide their adjustment. A low knowledge person, for example, might not even know if the anchor is high or low. A high knowledge person, on the other hand, might be quite confident about whether the anchor is too high or too low. Therefore, it seems reasonable that the anchoring and insufficient account should be revised to include a consideration of a person's knowledge level.

To a small degree, this was done in a recent revision to the anchoring and insufficient adjustment account. Simmons et al. (2010) described a model that was designed to explain when participants will effortfully adjust from a given anchor. In their updated account, after exposure to the anchor, people generate a preliminary estimate. If people feel this estimate is sufficiently accurate, they use this as their final estimate. If people feel this answer is not accurate enough, they adjust their estimate to another value. The important addition of this updated account is to suggest that the certainty that people have in the direction of the adjustment will moderate whether further adjustment will move away from or towards the anchor value. For example, if a person thinks his preliminary estimate is not far enough away from the anchor value, he will adjust farther away from the anchor when providing his final estimate. In contrast, if a person thinks her preliminary estimate is too far away from the anchor value, she will adjust closer to the anchor when providing her final estimate.

While relatively simple, this revision to the anchoring and insufficient account was important because it helped when explaining the effect of accuracy incentives on anchoring effects. Previous research found that incentives for accuracy did not influence the magnitude of anchoring effects from provided anchors (e.g., Epley & Gilovich, 2005; Tversky & Kahneman, 1974). This finding is surprising because one might expect that people who are given incentives for accurate responses would show reduced anchoring effects. An examination of these studies, however, revealed that the questions used were generally quite difficult (e.g., "What percentage of African countries are members of the United Nations?"). In a series of studies, Simmons et al. (2010) demonstrated that incentives for accuracy can reduce anchoring effects, but only when people know which way they should adjust from the anchor value. In one study, for example, anchors were either introduced in questions (e.g., "Is the length of the Mississippi River greater or less than 1200 miles?") or statements indicating the direction of adjustment (e.g., "The length of the Mississippi River is greater than 1200 miles"). Half of the participants were provided an incentive for providing accurate estimates. Simmons et al. found that the accuracy incentive did not affect judgments when the anchor was introduced in a question—as is the case in most previous anchoring research. However, when introduced in a statement indicating the direction of adjustment, participants who were given accuracy incentives exhibited smaller anchoring effects than the participants who did not get accuracy incentives. Presumably, when people were certain about which way to adjust their estimate, the incentives for accuracy increased their adjustment away from the provided anchor, thereby reducing their anchoring effects.

Simmons et al.'s (2010) concept of certainty about the direction of adjustment is certainly related to knowledge level. That is, someone who is more knowledgeable will also be better able to judge the direction he or she should adjust from a given anchor. Therefore, incentives for accuracy would be effective at increasing adjustment for a high knowledge participant, but not for a low knowledge participant (because he is unsure whether he should adjust further away from or closer to the anchor value). Disentangling whether knowledge or certainty in direction of adjustment is the critical factor would be quite difficult as these are surely related to one another. However, this might be a worthwhile goal for future studies.

I should point out that while Simmons et al.'s (2010) account does help specify when incentives for accuracy might influence adjustment, it does not account for the fact that high knowledge participants—without any incentives for accuracy—will be less influenced by anchors than low knowledge participants. Therefore, even though their account is an improvement over the previous anchoring and insufficient adjustment account, it cannot explain the results of Studies 1, 2, and 3.

Practical Implications for Debiasing Anchoring Effects

In addition to the theoretical implications described above, the current studies have practical implications. Anchoring effects have been observed in numerous real-world settings such as realtors' estimates of home prices (Northcraft & Neale, 1987), legal experts' sentencing decisions (Englich et al., 2006), doctor's diagnoses (Brewer, Chapman, Schwartz, & Bergus, 2007), consumers' willingness-to-pay for products (Ariely et al., 2003; Simonson & Drolet, 2004), and personal injury damages awards (Chapman & Bornstein, 1996; Marti & Wissler, 2000). Therefore, finding ways of reducing anchoring effects is very important. However, anchoring effects are quite resistant to debiasing manipulations including forewarning people about their biasing influence (e.g., Wilson et al., 1996) or providing incentives for accuracy (e.g., Epley & Gilovich, 2005; Tversky & Kahneman, 1974). In contrast to these studies, Studies 1, 2, and 3 demonstrated that manipulations of knowledge level significantly decreased participants anchoring effects. Therefore, a potential debiasing strategy for reducing anchoring effects could be to increase people's knowledge about the topic.

A situation where anchoring effects are quite costly is in personal injury damages awards. In general, the more money a plaintiff requests as compensation for their pain and suffering, the more money they are awarded by jurors (Chapman & Bornstein, 1996; Hinsz & Indahl, 1995; Malouff & Schutte, 1989). This tendency occurs even when controlling for the severity of the injury, resulting in high variability in awards for similar cases (Saks, Hollinger, Wissler, Evans, & Hart, 1997). If we assume that the amount of money a plaintiff is awarded should be most influenced by the severity of their injury, interventions designed to reduce anchoring effects seem worth implementing. The current studies suggest that a simple and effective intervention would be to give jurors brief descriptions of several cases including the amount of the award given to the plaintiff (analogous to the full-knowledge conditions in Studies 1 and 3). In fact, this intervention could be even simpler and only give the jurors the amount of money awarded to the plaintiff without any description of the details of the case (similar to the distribution condition in Study 3). Presumably, this would be enough to increase the jurors' metric knowledge as to what appropriate awards are. They should, therefore, be less influenced by the amount of money requested by plaintiff than if they had not received information about previous awards.

Final Thoughts

Most would agree that knowledge is good and bias is bad. It also seems reasonable to assume that more knowledgeable people should be less biased. However, the studies in this dissertation illustrate that this is not always the case. The relationship between knowledge and anchoring effects is complex because not all types of knowledge are equally effective at reducing the biasing influence of anchors. Knowing this, researchers can now make better predictions about the moderating role of knowledge—and other factors—in anchoring studies. Furthermore, these findings can guide practitioners in developing debiasing techniques that effectively reduce the biasing influence of anchors. In conclusion, increased knowledge is important, but only the right type of knowledge can reduce bias.

APPENDIX A

LISTS OF AFRICAN COUNTRIES USED IN STUDY 1

List A			List B		
Country	Population (in millions)	Capital City	Country	Population (in millions)	Capital City
Ethiopia	85	Addis Ababa	Egypt	80	Cairo
Tanzania	38	Dodoma	Sudan	39	Khartoum
Kenya	35	Nairobi	Algeria	33	Algiers
Ghana	23	Accra	Uganda	28	Kampala
Mozambique	20	Maputo	Cameroon	18	Yaoundé
Zambia	15	Lusaka	Angola	16	Luanda
Niger	14	Niamey	Mali	14	Bamako
Malawi	13	Lilongwe	Senegal	12	Dakar
Somalia	10	Mogadishu	Guinea	9	Conakry
Rwanda	8	Kigali	Benin	8	Porto Novo
Togo	6	Lomé	Libya	6	Tripoli
Liberia	3	Monrovia	Mauritania	3	Nouakchott

APPENDIX B

INSTRUCTIONS USED IN STUDY 2

Irrelevant and relevant-weak conditions:

Thank you for agreeing to participate in this survey. You will be asked questions regarding your thoughts and feelings about a variety of cars. To give you a frame of reference when going through this survey, we have provided you with a list of five new cars currently sold in the U.S. Please take a couple minutes and review the information below. Once you have done this, click on the Next button below.

Relevant-strong condition:

Thank you for agreeing to participate in this survey. This survey consists of two parts. In the first part, you will see information about a number of cars currently sold in the U.S. In the second part, you will be asked questions regarding your thoughts and feelings about a variety of cars.

Make sure to review the information below carefully as we will ask you questions about this information later. This is a short survey, so please take your time when reviewing the information and answering questions. Please take some time now and review the information below. Once you have done this, click on the Next button to proceed to the second part of the survey.

APPENDIX C

STIMULI PRESENTED IN STUDY 2

Irrelevant condition

Car	Photo	Worldwide Sales (2011)
Chevrolet Cruze LS Sedan		17,000
Ford Fusion S Sedan		20,600
Honda Accord LX Sedan		22,700
Volkswagen Passat Sedan		27,900
Acura TSX Sedan		30,500

Relevant-weak and
Relevant-strong conditions

Car	Photo	Base Price
Chevrolet Cruze LS Sedan		$17,000
Ford Fusion S Sedan		$20,600
Honda Accord LX Sedan		$22,700
Volkswagen Passat Sedan		$27,900
Acura TSX Sedan		$30,500

APPENDIX D

LIST OF AFRICAN COUNTRIES USED IN STUDY 3

Country	Population (in millions)	Capital City
Ethiopia	85	Addis Ababa
Egypt	80	Cairo
Sudan	39	Khartoum
Tanzania	38	Dodoma
Kenya	35	Nairobi
Uganda	28	Kampala
Ghana	23	Accra
Mozambique	20	Maputo
Cameroon	18	Yaoundé
Angola	16	Luanda
Zambia	15	Lusaka
Malawi	13	Lilongwe
Senegal	12	Dakar
Somalia	10	Mogadishu
Togo	6	Lomé
Mauritania	3	Nouakchott

APPENDIX E

LISTS OF STATES USED IN STUDY 4

States used in measurement phase

List A		List B	
State	Population (in millions)	State	Population (in millions)
Texas	25.1	Florida	18.8
North Carolina	9.5	Michigan	9.9
Washington	6.7	Virginia	8.0
Missouri	5.9	Arizona	6.4
Alabama	4.8	Colorado	5.0
Oregon	3.8	Louisiana	4.5

States used in the testing phase

List C			
State	Population (in millions)	High Anchor	Low Anchor
Pennsylvania	12.7	25	6
Ohio	11.5	23	5
New Jersey	8.8	17	4
Indiana	6.5	13	3
Wisconsin	5.7	11	3
Connecticut	3.6	7	2

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