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The role of "Prominent Numbers" in open numerical judgment: Strained decision makers choose from a limited set of accessible numbers☆

Benjamin A. Converse[a,b,*], Patrick J. Dennis[c]

[a] Frank Batten School of Leadership and Public Policy, University of Virginia, 235 McCormick Road, PO Box 400893, Charlottesville, VA 22904, United States
[b] Department of Psychology, University of Virginia, 485 McCormick Road, PO Box 400400, Charlottesville, VA 22904, United States
[c] McIntire School of Commerce, University of Virginia, 125 Ruppel Drive, Charlottesville, VA 22904, United States

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ABSTRACT

Numerate adults can represent an infinite array of integers. When a judgment requires them to "pick a number," how do they select one to represent the abstract signal in mind? Drawing from research on the cognitive psychology of number representation, we conjecture that judges who operate primarily in decimal systems simplify by initially selecting from a set of chronically accessible "Prominent Numbers" defined as the powers of ten, their doubles, and their halves [… 5, 10, 20, 50, 100, 200…]; then, when willing and able, refining from there. A sample of 3 billion stock trades reveals that traders' decisions reflect Prominent-Number clustering (Study 1) and a "natural experiment" reveals more clustering in rushed trading conditions (Study 2). Three sets of subsequent studies provide evidence consistent with an accessibility-based account of Prominent-Number usage: Experiments show that judges rely more on Prominent Numbers when they are induced to rush rather than take their time (Studies 3a and 3b), and when they are under high versus low cognitive load (Studies 4a, 4b, and 4c); and a final correlational study shows that Prominent-Number clustering is more apparent for judgments that require judges to scan a wider range of plausible values (Study 5). This work underscores the need to differentiate between Round Numbers and Prominent Numbers, and between representational properties of graininess and accessibility, in numerical judgment.

1. Introduction

Judgments and decisions often require the selection of a single number. An investor decides how many shares of stock to buy. A potential homebuyer predicts how much a kitchen renovation might cost. A negotiator in a fast-paced bargaining session determines the value of a newly-introduced side issue. Numerate adults have the capacity to represent an infinite array of integers. When they are asked to "pick a number, any number," how do they arrive at a specific representation of the abstract signal they have in mind?

A long line of research on anchoring-and-adjustment indicates that people can often "arrive at a reasonable estimate by tinkering with a value they know is wrong" (Epley & Gilovich, 2001, p. 391). But, perhaps just as often, the judgment at hand does not systematically activate a memory-based internal anchor, nor does it occur in the context of an informative external anchor.[1] In other words, for many judgments, judges may not have an obvious wrong value to "tinker with." A different model may be needed to understand this class of judgments that occur when neither memory nor the environment provides a ready starting place from which to adjust. We refer to such judgments as *open numerical judgments*. Despite—or possibly because of—longstanding interest in the anchoring bias, little attention has been paid to this class of unanchored judgments (cf. Stewart, Chater, & Brown, 2006). Our central aim in the current work is to examine a potential shortcut that people may spontaneously employ to simplify open numerical judgments.

We propose here that people simplify open numerical judgments by initially considering a limited set of chronically accessible numbers. Satisficing in this judgment—that is, accepting that the offered judgment may represent a relatively coarse approximation of the signal in mind—would involve considering only the most-limited set of highly accessible numbers. In contrast, given the opportunity and willingness to produce a more precise approximation, increased deliberation would involve considering more densely populated sets of decreasingly

☆ Data files, code, and original materials are available on the *Open Science Framework* at https://osf.io/kfb84/.

* Corresponding author at: Frank Batten School of Leadership and Public Policy, University of Virginia, 235 McCormick Road, PO Box 400893, Charlottesville, VA 22904, United States
E-mail addresses: converse@virginia.edu (B.A. Converse), pjd9v@virginia.edu (P.J. Dennis).

[1] Implausible values can also affect numerical judgments (Chapman & Johnson, 2002; Tversky & Kahneman, 1974), but they do so by increasing the accessibility of consistent information, not by introducing a starting point (Epley, 2004; Mussweiler & Strack, 1999).

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accessible numbers. This outline of an accessibility-based model builds from the idea that people have more detailed representations of some numbers than others (Dehaene & Mehler, 1992) and that a logarithmic function provides a good description of the mental space in which people represent numbers (Banks & Coleman, 1981; Dehaene, 2001, 2003, 2007; Nieder & Miller, 2003; Piazza, Izard, Pinel, Le Bihan, & Dehaene, 2004).

Our conjecture is that, for people who primarily operate in a decimal (i.e., base-10) system of numbers, the chronically accessible set of numbers that they initially scan, and thus disproportionately rely on, is defined in theoretical work on "the prominence structure of the decimal system" (Albers & Albers, 1983; also Albers, 1997, 2001). Specifically, the "Prominent Number" set under consideration includes the powers of ten […10; 100; 1000…], their doubles […20; 200; 2000…], and their halves […5; 50; 500…]. Formally, this sequence […5; 10; 20; 50; 100; 200; 500; 1000; 2000…] can be represented as $n10^i$, where i is any integer and n is ½, 1, or 2. Albers and colleagues' treatment of these numbers in decision making focused on the convenient mathematical property that all integers can be constructed as a sum of non-repeated combinations of the Prominent Numbers using coefficients −1, 0, or +1. For example, 1400 = 1000 + (1 * 500) + (0 * 200) + (−1 * 100). Our treatment, in contrast, emphasizes the psychological (i.e., representational) properties of the numbers (Dehaene & Mehler, 1992), properties that may in fact lead people to rely disproportionately on the set when making open numerical judgments.

We began developing this model as a way to understand our initial observation (presented in Study 1) that stock trade quantities cluster disproportionately on the Prominent Numbers. Previous researchers have observed that certain numbers, including 10, 20, and 50, appear disproportionately in written language (Dehaene & Mehler, 1992; Jansen & Pollmann, 2001), visual ratio estimations (Baird, Lewis, & Romer, 1970), hypothetical willingness-to-pay estimates (Whynes, Philips, & Frew, 2005), and guesses about what numbers other people would select within a given range (Baird & Noma, 1975). They also appear to feature as common rounding values in heuristic-based decision processes (Albers, 2001; Brandstätter, Gigerenzer, & Hertwig, 2006). However, there is little clarity about whether these disparate observations identify the same, separate, or partially overlapping phenomena; and none of the accompanying accounts address open numerical judgments in general. As we sought to better understand our initial empirical result, and to try to understand how these various phenomena may or may not relate to it, we identified this as an opportunity to produce a preliminary sketch of a general model of open numerical judgments.

We first review studies from cognitive and social psychology that motivate our accessibility-based model and the specific Prominent-Number conjecture within that model. We then present seven studies that assess the potential usefulness of the proposal by testing two predicted implications for open numerical judgments. The first implication is that distributions of open numerical judgments should disproportionately cluster on the Prominent Numbers. Even if only a small proportion of a large sample of judges terminates the search after considering only the most-accessible numbers, then more judgments than expected by chance would end on one of the Prominent Numbers (more so, even, than on other Round Numbers in the vicinity). The second implication is that Prominent-Number clustering should be more apparent under conditions that favor the use of highly accessible concepts. Thus, when judges cannot or will not invest additional cognitive effort in refining their judgments, or when the judgment itself imposes a greater cognitive burden by requiring the judge to scan a wider array of plausible values, Prominent-Number clustering should increase.

1.1. From 'at-large scanning' to 'preferential representation'

Consider the dilemma of producing a numerical judgment on the fly with no accessible anchor from which to adjust. How might one proceed? For illustration, one possibility is that the judge mentally scans the full number line to find a reasonable match to the abstract signal in mind. But, without an anchor to start from, where would the judge start? At 1 and move up? At the highest number she can think of (*1 billion*? *1 trillion*?) and move down? At a random number somewhere in between? Such an account is obviously unrealistic. It would be wildly inefficient from a cognitive standpoint. From a behavioral standpoint, it would probably be mind-numbingly slow.

More to the point, an at-large scanning process is not consistent with a great deal of work on how people use and represent numbers. Research from both cognitive and social psychology has demonstrated that not all numbers are represented equally (Dehaene & Mehler, 1992; see also Schelling, 1960). Thus, at-large scanning is not a likely candidate for how open numerical judgments actually proceed. It stands to reason that open numerical judgment might be simplified through the preferential representation of certain numbers. For intuition, consider an interactive digital map. When zoomed way out, the map shows only some of the major cities. Other cities do not cease to exist, but they are not represented until one zooms in. For example, when we looked at a map of Spain while zoomed out, the edges of the map showed the tip of Maine and the west coast of India, and only the cities of Madrid and Barcelona were visible within Spain. Zooming in one level restricted the range, now framed by the Atlantic Ocean in the west and Turkey to the east, and brought more cities into view. Seville, Granada, Málaga, and Valencia were now visible alongside Madrid and Barcelona. At one more level of zoom, less Atlantic Ocean was visible to the west and the map onlyextended to Italy in the east, and nearly 30 cities become visible within Spain.[2] With respect to the number line, we compare the Prominent Numbers to the major cities. When people are "zoomed way out" (i.e., in the initial step of an open numerical judgment), we suggest that the major units they see are some subset of […50; 100; 200; 500; 1000; 2000…]. The numbers in between can be "seen" (i.e., become more accessible) as people "zoom in" (i.e., refine), but this requires cognitive effort. The potential efficiency gain over at-large scanning is obvious.

1.1.1. Detailed representation and accessibility

> *The internal representation of numbers is compressive and akin to Fechner's law, that is, it is more detailed for small numbers than for large ones.* (Dehaene & Mehler, 1992, p. 19).

Consistent with the intuition of commonly used language, cognitive science suggests that numerate adults mentally organize quantities along some continuum, or "mental number line" (Dehaene, Bossini, & Giraux, 1993; Dotan & Dehaene, 2016). The number line in people's heads, however, may be quite different from the version that hangs on the walls of elementary school classrooms. The latter is linear in its scaling, representing every integer with equal detail. The former, according to both behavioral and neuroscience studies, represents certain numbers with more detail than others, with the numerical distance between the preferentially-represented values getting further and further apart as magnitude increases (Dotan & Dehaene, 2016). In the same way that people perceive the difference between two relatively quiet sounds to be greater than the equivalent difference between two relatively louder sounds (i.e., the "Weber-Fechner Law"), people also perceive the difference between two relatively small numbers to be greater than the equivalent distance between two relatively large numbers (Krueger, 1989; Shepard, Kilpatric, & Cunningham, 1975). While there is ongoing debate about the most precise way to mathematically describe this mental compression, a logarithmic function provides a good account (Banks & Coleman, 1981; Dehaene, 2001,

[2] As we were researching this example on Google Maps, we could not help but notice that the unit Google scales to moves successively from 1000 mi., 500 mi., 200 mi., 100 mi., 50 mi., 20 mi., 10 mi., 5 mi., 2 mi., 1 mi., 2000 ft., 1000 ft., … down to 20 ft.

2003, 2007; Nieder & Miller, 2003; Piazza et al., 2004). Thus, the objective (linear) distance between the "major" units on the mental number line would increase for subjectively larger quantities.

1.1.1.1. Candidates for prominence. Mathematically, there are countless (quasi-)logarithmic sequences that adults could rely on as benchmarks. How did […5, 10, 20…] become the privileged ones? Why are they the Prominent Numbers rather than some other set? We can only speculate here, but we suspect the general principle that determined this outcome was cognitive ease; and the specific numbers that cognitive ease "selected" were based on a confluence of chance, culture, and evolution. Given that we happen to operate in a base-10 system, and given that we appear to engage in logarithmic representation, this particular set of numbers—the powers of the base and their halves and doubles—provides good coverage of the number line with a minimum of computational complexity. To see what we mean by good coverage, consider that on a logarithmic scale, 200 is 30% of the way from 100 to 1000; and 500 is 70% of the way. This pattern continues at every order of magnitude: for example, 2000 is 30% of the way from 1000 to 10,000; and 5000 is 70% of the way.[3] In a log-10 space, where the powers of ten (10^i) are, by definition, equally spaced, adding $(1/2) * 10^i$ and $2 * 10^i$ as major benchmarks provides almost equally spaced coverage along that log-scaled line. And, satisfying the basic need to navigate the space with cognitive efficiency, this happens to work using what we assume are two of the simplest multiplicative operations, halving and doubling. It seems likely that numerate adults in base-10 cultures can double or halve any power of ten with ease, and it is probably no cultural or evolutionary coincidence that they could rely on their ten fingers, two hands, (and five fingers per hand) to help them navigate this scale if needed (see Ifrah, 1981; Previtali, Rinaldi, & Girelli, 2011). It seems it would be hard to engineer a set of numbers that better balances coverage and ease within the decimal system.

If things had worked out differently in our cultural—evolutionary history, however, a different set of Prominent Numbers would likely have emerged. If evolutionary forces had instead conspired to give humans twelve fingers, for example, or if we had committed behaviorally to counting by using our thumbs to point to the twelve phalanges of our other four fingers, perhaps we would have more fully embraced a dozenal system (also called duodecimal; see Dehaene, 2011). In this case, preferential representation would probably have developed for a different set of Prominent Numbers. Perhaps in this case, that set would have conformed to the same scaling rule of "the base number and its doubles and halves." In a dozenal system, these numbers would be […6, 12, 24, 72, 144, 288…]. This set probably does not look particularly prominent to the base-10-trained eye, but when stated as "…half a dozen, one dozen, two dozen, half a gross, one gross, two gross…" a decimal thinker begins to get the intuition.[4] In this system, the halves and doubles provide only slightly less convenient spacing than in the decimal system. "Two gross" (i.e., 288) is 28% of the way between the base-number "one gross" (i.e., $12^2 = 144$) and the next base-number "one great gross" (i.e., $12^3 = 1728$); and "half a great gross" (i.e., 864) is 72% of the way.[5]

Halves and doubles are not invariably convenient, however. The larger the base-number in a given system, the less even is the coverage provided by the halves and doubles. Imagine, instead, if millions of years from now, the continued evolution of our brains and culture lead us to scrap the decimal system and adopt a hexadecimal (base-16) system like many computer programming applications. Perhaps in this case, halving and doubling the powers of the base does not provide sufficient coverage of a logarithmic number line. In this system, doubling a base gets you to a place 25% of the way to the next base and halving the next base gets you to a place 75% of the way between the two, leaving a sizable unmarked gap in the middle. Perhaps at this point, there is not enough coverage in the middle and a "quad" factor would be needed so often to split the difference (e.g., multiplying a base times four gets you 50% of the way between two bases) that it too would become one of the chronically accessible Prominent Numbers.

Our goal with these thought experiments is merely to clarify that the "Prominent Number" category is only descriptive. To trace its etymology we can speculate about the joint evolution of minds and culture, but cannot be sure about what numbers would have risen to Prominence if chance had pushed minds or culture along a different path. Importantly, we do not think there is anything *inherently* prominent about […5, 10, 20…], except in the context of a base-10 number system and logarithmic mental scaling of that system.

1.1.1.2. From prominence to chronic accessibility. If […5, 10, 20…] are indeed the numbers that people scale to—the vivid, persistent "major units" on their mental number line—then it follows that they should be chronically accessible (Koriat, 1993). The notion of *chronic* accessibility refers to the idea that a given construct (here, a number) is "ready" to come to mind across multiple contexts (e.g., judgments, conditions; Bargh, 1984; Higgins & King, 1981), rather than just in certain judgments. It is assumed to develop from frequent and consistent experience with the construct. This provides a useful contrast with numbers that may be highly accessible in some contexts, but not others. For example, it should not be hard to temporarily increase the accessibility of dozens (and their doubles and halves) by asking people how many bagels, donuts, or chicken wings they want; or to temporarily increase the accessibility of sixties (and their doubles and halves) by asking how many minutes something will take. But outside idiosyncratic contexts such as those, we would not expect to see disproportionate clustering on dozenal bases nor sexagesimal bases among decimal users. In other words, we acknowledge potentially high variation in the context-based (or, temporary) accessibility of most numbers, but assume that in a decimal society there is relatively less variation in the representation-based (or, chronic) accessibility of the Prominent Numbers. Thus, one way in which Prominent Numbers are represented differently than other numbers is that they should be highly accessible across people, judgments, and contexts.

1.1.2. Graininess, roundness, and prominence

> *Some numerals, called reference numerals, are used not only to refer to precise numerosities, but also to approximate wide ranges of numerosities* (Dehaene & Mehler, 1992, p.19).

A second key property of number representation is that some numbers are more readily understood to, at times, represent a wider range of other numbers. For instance, one study demonstrated that people prefer sentences such as "900 is approximately 1000" to sentences such as "1000 is approximately 900" (Rosch, 1975), apparently indicating that certain numbers are more likely to be considered as coarsely-grained reference values (e.g., 1000) than others (e.g., 900). Based on these regularities, numbers can sometimes convey not only quantity information but also the potential precision with which that quantity is being communicated (Bruine de Bruin, Fischoff, Millstein, & Halpbern-Felsher, 2000; Fox & Rottenstreich, 2003; Jerez-Fernandez, Angulo, & Oppenheimer, 2014; Welsh, Navarro, & Begg, 2011; Yaniv & Foster, 1995; Zhang & Schwartz, 2013). For example, the proud owner of a new television who says, "I paid a thousand bucks for it," could possibly mean that he paid precisely $1000; but he more likely means that he paid approximately $1000 (perhaps, but not necessarily, implying $900–$1100). In contrast, a proud owner who says, "I paid $960

[3] Represented mathematically, $\log_{10}(200) = 2.30$, $\log_{10}(500) = 2.70$, $\log_{10}(2000) = 3.30$, $\log_{10}(5000) = 3.70$.

[4] Further, if we used a dozenal system, then we would express those numbers using a place system built on a "dozens" place and a "gross" place instead of a "tens" places and "hundreds" place, so they would look more round. For example, "twenty-four" would be annotated as "20" in a dozenal system (2 dozens and 0 ones); and "two hundred eighty-eight" would be annotated as "200" (2 grosses, 0 dozens, 0 ones).

[5] Represented mathematically, $\log_{12}(288) = 2.28$ and $\log_{12}(864) = 2.72$.

for it," probably means that she paid precisely $960 (or, maybe $955–$965). Without providing any explicit information about confidence, units, or ranges, a speaker can convey such information by her number selection. The Prominent Numbers appear to be among these coarser reference values (Dehaene & Mehler, 1992; Jansen & Pollmann, 2001; Sigurd, 1988), prompting the need to consider whether any observed Prominent-Number clustering is due to accessibility or communicated coarseness.

1.1.3. Clarifying terms: mathematical versus representational properties

The terms *roundness* and *graininess* have both been used in the literature to refer to the subjective property of a number seeming less precise. For clarity, we reserve *roundness* to refer to the mathematical precisision with which a number is expressed. To define roundness, we invoke the term *significant figures* to refer to all of the digits in a number that are not trailing zeroes (e.g., 303 has three significant digits, 300 has only one), and, in turn, we operationalize the dimension that runs from roundness to precision by the number of significant figures (hence, 303 is "less round" or "more precise" than 300). In contrast, we reserve the language of *graininess* (Yaniv and Foster, 1995) to refer to the subjective representational property of the number. Numbers that are *coarse* approximate wider rangers of numerosities in one's mind than numbers that are *fine*.

Also for clarity, we will use the capitalized term *Round Numbers* as a linguistic shortcut to refer to the set of numbers that has only 1 significant figure (formally, $n10^i$, where i is any integer and n is any integer 1…9). This shortcut is useful because it parallels our use of the capitalized term *Prominent Numbers* to refer to the specific set […5, 10, 20…]. Based on these specifications, the Round Numbers, which include the Prominent Numbers as a subset, are both the *roundest* and the *coarsest* numbers at any given magnitude. This also allows us to specify the set of *Non-Prominent Round Numbers* (formally, $n10^i$, where i is any integer and n is 3, 4, 6, 7, 8, or 9), which have the same roundness as the Prominent Numbers at any given magnitude and therefore provide a valuable comparison group.

1.1.4. Parsing accessibility and coarseness

Given that the Prominent Numbers are high on both accessibility and coarseness, we will have to carefully consider whether any observed Prominent-Number clustering reflects an accessibility-based shortcut or, alternatively, the intent to communicate a wider confidence interval. It is important to note the difference between a communication-based explanation and incidental coarseness. Judgments driven by accessibility will necessarily approximate wide ranges. For example, if a judge asked to estimate the population of Chicago (2.7mm) only considers the Prominent Numbers 1mm, 2mm, and 5mm, and chooses "2 million," as her answer, this necessarily represents a wide range (perhaps 1.5mm–3.5mm). However, based on the final answer alone, it is also possible that the judge "zoomed way in," perhaps even considering estimates as specific as 2.4mm. If she ultimately decided, however, that she was not confident enough to narrow the range that much, she might offer the coarser, less informative "2 million" to avoid inaccuracy (Yaniv & Foster, 1995). At face-value, we cannot know whether the coarse "2 million" was selected because of its accessibility or because of the relative coarseness it communicates.

We argue that the communication-based explanation is not compelling in the stock context—a bid for 500 shares of stock might reflect a coarse choice between 500 or 1000 shares, but not a desire to communicate uncertainty about buying "somewhere between 400 and 600 shares"—but in our other studies, we have to consider whether participants might choose Prominent Numbers to communicate to the researchers that they are unsure about their judgment. To better determine what might be driving clustering in these contexts, we exploited the partial overlap of the Prominent Numbers and the Round Numbers and, more specifically, the assumption that the Prominent Numbers are more accessible, but not necessarily systematically coarser than the Round Numbers.[6] To the extent that some set of conditions (e.g., cognitive load) increases Prominent-Number clustering demonstrably more than Round-Number clustering, we can infer that the variance is attributable to differences in accessibility more so than graininess. A potential weakness of this discriminant-validity approach is that it presupposes no systematic difference in perceived graininess between the Prominent Numbers and the other Round Numbers. While we know of no studies that systematically document such a difference, and while our own attempts to document such a difference failed to systematically do so (see Studies S1, S2a, and S2b in the Supplemental Online Materials (SOM)), we cannot definitely rule out that such a difference exists. Thus, discriminant validity provides an important but not definitive clue. To supplement discriminant validity on the dependent variable side, we also aimed for discriminant validity on the independent variable side. In a series of experiments, we employed manipulations that have been closely linked to the use of accessible mental constructs, namely time pressure in Studies 2a and 2b and cognitive load in Studies 3a, 3b, and 3c (Epley & Gilovich, 2006; Gilbert & Gill, 2000; Gilbert, 2002; Kruger, 1999). We discuss the relative strength of the accessibility-based interpretation in each study.

1.2. Research overview

Across studies, we examined numerical judgments in a variety of contexts that we think are relatively "open." That is, we assume these judgments do not systematically activate strong anchors for most judges. First, this does not necessarily mean that *no* potential reference values come to mind other than the Prominent Numbers; but, rather, that no values come to mind as "close-but-wrong" starting places (cf., Epley & Gilovich, 2001). Second, this does not necessarily mean that *none* of the judges in our sample will rely, idiosyncratically, on a close-but-wrong starting place. We expect that certain individuals in certain contexts will use their own anchors—whether a bit of idiosyncratic knowledge, a memory of a relevant past judgment, or some other starting place—but we tried to select judgments for which this would be the exception rather than the rule (see Epley & Gilovich, 2001, 2006; Jacowitz & Kahneman, 1995). To the extent that individuals were using self-generated anchors in any particular setting that we studied, this should lead us to underestimate the extent of Prominent-Number clustering for judgments that are actually open.

In Study 1, we capitalized on the availability of a massive archive of open numerical judgments to determine whether Prominent Numbers are disproportionately represented. We examined over 3 billion stock trades to determine if they cluster on the Prominent Numbers. We found that they did and that this clustering was more pronounced on the Prominent Numbers than on adjacent Non-Prominent Round Numbers. The overarching goal of our subsequent studies was to examine the validity of an accessibility-based account for this Prominent-Number clustering. In Study 2, we exploited a natural manipulation of trading conditions to test whether Prominent-Number clustering is more apparent when traders are presumed to be rushing. Next, Studies 3–5 investigated the role of cognitive investment, which should decrease the influence of accessibility on judgment outcomes, by manipulating or measuring time pressure, cognitive load, and the range of plausible values that judges needed to scan.

[6] We note here that some linguists have put forth mathematical derivations of "roundness" that would suggest the Prominent Numbers are perceived as "rounder" (in our terms, coarser) than other numbers (Jansen & Pollmann, 2001; Sigurd, 1988). However, these approaches seem to use the term "roundness" in a way that conflates graininess and accessibility. Importantly, neither derivation includes a strong empirical demonstration that people systematically perceive the Prominent Numbers as coarser than adjacent Non-Prominent Round Numbers.

2. Study 1: Trade size clustering

Normative portfolio theory assumes that investors select portfolios to maximize expected return at an acceptable level of risk (Markowitz, 1952). To illustrate, an investor with a \$100,000 portfolio might decide to invest five percent of her wealth in Apple stock. She would divide the \$5000 allocation by Apple’s share price (\$106.94 at the time of this writing) to determine her purchase size: 46 shares. In practice, however, we assume that investors often think of trade quantities directly: “How many \$106.94-shares of Apple do I want?” While we cannot definitively rule out the possibility of anchors influencing this judgment, there are not many compelling candidates other than past trades. But then the question remains, why was the past trade size a Prominent Number? In other words, our working assumption is that many trades reflect open numerical judgments. If so, and if the Prominent-Number conjecture is correct, then trades should cluster on the Prominent Numbers.

2.1. Method

We examined all stock trades in the Trade and Quote (TAQ) database for the 125 trading days between January 4, 2011 and June 30, 2011 (the most recent six-month period of data available to us). The TAQ database contains all trades that occur for stocks listed on the New York Stock Exchange, American Stock Exchange, and the Nasdaq National Market System. We observed trades in the TAQ database that have a price and size greater than zero and that occur between 9:30 a.m. and 4:00 p.m. To keep the dataset manageable, we only examined trades with sizes between 200 and 10,000 shares (and added 100-share trades and 11,000-share trades as respective proximal comparisons). Each firm has an average of 4283 of trades (96%) that are integer multiples of 100 (round-lots) and 199 trades (4%) that are not integer multiples of 100 (odd-lots). We ignored odd-lot trades because they represented such a small percentage of trades. Our final dataset includes 3.2 billion trades with an average of 5735 unique firms each day.

We used daily trade-size frequencies as the basic unit of observation. We normalize this way to avoid undue influence from firms with high volume (e.g., Bank of America trades more than 60 million shares per day) relative to those with low volume (e.g., National Bank of Canada trades fewer than 3000 shares per day). For example, if a few high-volume stocks like Bank of America tend to trade in Prominent Numbers, whereas most low-volume stocks do not, this normalization would help us avoid drawing false general conclusions about Prominent-Number clustering. While other analytic approaches might be more efficient statistically, this approach is unbiased and consistent, and has the advantage of relative simplicity.

To aggregate to daily trade-size frequencies, we started by counting the number of trades that occurred in each trade size (100; 200; … 9900; 10,000; 11,000) for each day for each firm, resulting in one observation with the number of trades in each size for each firm-day. We then divided these counts by the total number of trades for that firm-day to obtain a frequency. The frequency of trades for each trade size is then averaged across all firms, resulting in one observation per day for each trade size. For example, imagine there are only two possible trade sizes, 100 and 200 shares. On Monday, National Bank of Canada has a total volume of 10 trades, 4 of which are 100 shares (40%) and 6 of which are 200 shares (60%). The same day, Bank of America has a total volume of 20 trades, 16 of which are 100 shares (80%) and 4 of which are 200 shares (20%). In this case, the average trade-size frequency for 100-share trades is (40% + 80%)/2 = 60% and the average trade-size frequency for 200-share trades is (60% + 20%)/2 = 40%.

Given that larger trades in a stock represent a greater share of an individual's wealth, as a baseline we would expect the frequency of a given trade size to decrease as trade size increases. Indeed, as expected, the distribution we observe does show that there are fewer 900-share trades than 800-share trades, fewer 800-share trades than 700-share trades, and so forth. But if traders’ decisions cluster on Prominent Numbers, then we would expect 1000-share trades to be more common than both 1100-share trades and 900-share trades. However, comparing frequencies directly is not a clean comparison for this decision. If there are fewer 1100-share trades than 1000-share trades, this could reflect Prominent-Number clustering, or it could simply reflect the fact that, on average, 1000-share trades represent a smaller portion of an investor's wealth. To test for a Prominent-Number bias, then, we needed a baseline for expected share-size frequency. To remain agnostic about the functional form of this baseline, we fitted a non-parametric regression to the data to estimate a baseline relationship between frequency and trade size. This allowed us to examine the residuals from that baseline to determine if Prominent-Number sized trades exceed the expected frequency more so than trades of proximal, but Non-Prominent sizes.

2.2. Results and discussion

To fit an empirically determined baseline curve to the data, we took the logarithm of the average frequency of trades in each size category for each day in the sample. We then estimated a non-parametric regression with a 3rd degree polynomial, an Epanechnikov kernel, and a bandwidth of 2000. We chose these parameters to balance our ability to capture the functional form without over-fitting. (See SOM for further explanation and robustness checks.) We calculated daily residuals for each trade-size as the difference between the expected value from the non-parametric regression and the actual value, resulting in 125 observations for each trade-size residual. Fig. 1 shows the fitted curve and corresponding average residuals. Note that the residuals would provide a conservative estimate of Prominent-Number clustering because inclusion of the Prominent-Number frequencies would “pull” the supposed baseline up, thus leading to underestimation of how much they actually deviate from expectation.

Large residuals at 1000; 2000; and 5000 are immediately apparent, but there are also large residuals at other Round Numbers, such as 3000 and 4000. It is unclear whether there is a specific preference for trading in Prominent Numbers or a more general preference for trading in Round Numbers. To test this, we compared average daily residuals for each Prominent Number in the observed range to the nearest Round Number (e.g., 500 versus 400 and 600; 5000 versus 4000 and 6000). We chose the closest Round-Numbered trade size for comparison because it provides variation in the number-type (Prominent vs. Non-Prominent) while holding economic constraints relatively constant. For example, we do not compare a trade size of 500 to a trade size of 900 because the latter represents an investment of almost twice as much money. Determining appropriate comparisons for 1000 and 10,000 poses a challenge and is discussed below.

Table 1 shows that each meaningful comparison is consistent with the Prominent-Number conjecture. Across all of these comparisons, the lowest t was obtained for 2000 versus 3000, $t = 8.39$, $p < .01$, with all other $|ts| > 45$, $ps < .001$. For example, the residuals from 500- and 5000-share trades are larger than those from 400- and 4000-share trades, respectively; and larger than those from 600- and 6000-share trades, respectively. We interpret this as evidence of more clustering on “5s” than on “4s” or “6s.” Comparing the “2s” to the “3s” provides similar evidence of more clustering on the “2s.”

Given the very small standard errors, effect sizes for each of these comparisons were quite large using a common metric. For example, for the 5000-versus-6000 comparison, Cohen’s $d_z > 4$; and for the 2000-versus-3000 comparison, Cohen’s $d_z = 0.75$. (Cohen’s d_z for other comparisons can be calculated directly from Table 1, using $t/\sqrt{(N = 125)}$, following Lakens (2013) and Rosenthal (1991)). To put this into perspective, on a daily basis, the number of 5000-share trades actually executed (~19.4k) is 12.0 times as high as the predicted number of trades (~1.6k). In contrast, the regression also underestimates the number of 6000-share trades, but not nearly as much. On

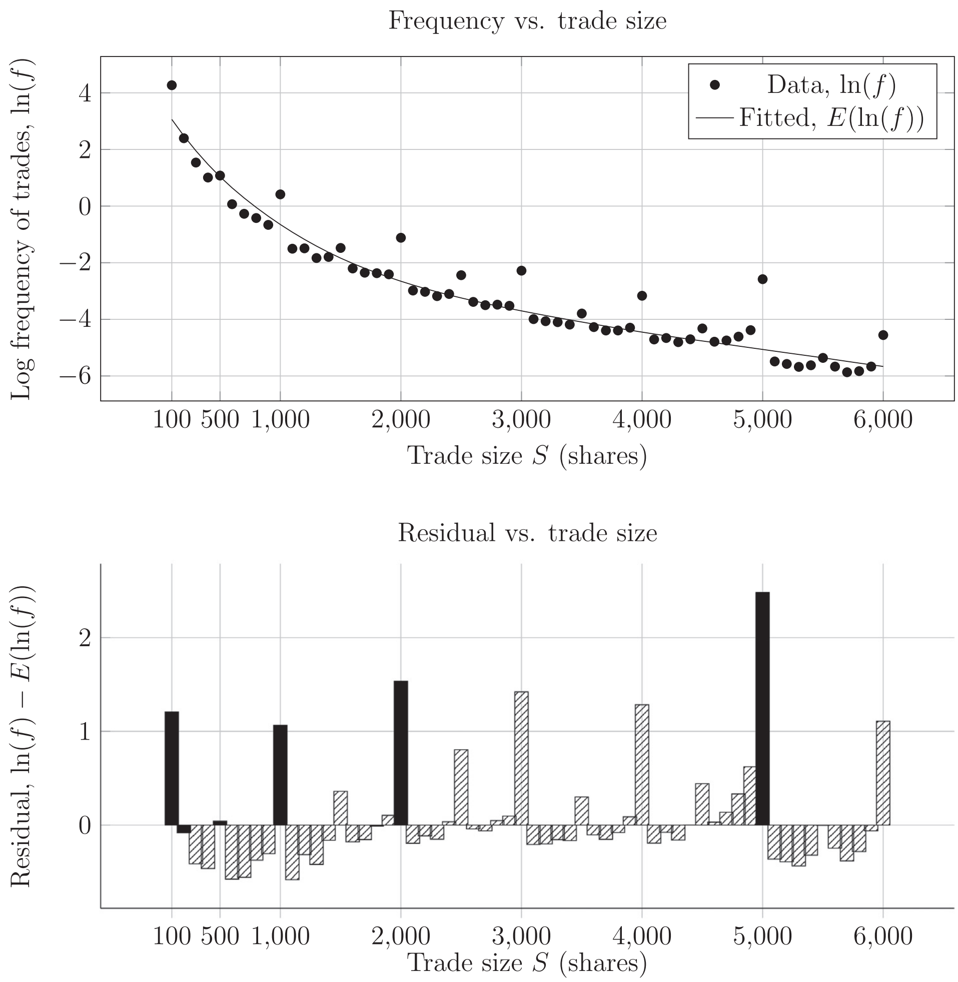

Fig. 1. Frequency and residuals vs. trade size. Note: The top plot shows the log of the frequency of daily stock trades for a particular size, ln(*f*), vs. trade size *S*. *f* is the frequency of trades of a particular size for a firm in a given day, averaged across the 125 trading days in our sample. The fitted function is obtained using a non-parametric regression with a 3rd degree polynomial, an Epanechnikov kernel and a bandwidth of 2000. The bottom plot shows the residual, ln(*f*) − *E*(ln(*f*)), from the non-parametric regression in the top plot. Prominent-Number sizes are shown in solid black, Non-Prominent sizes are shaded.

a daily basis, the number of 6000-share trades actually executed (~2.7k) is only 3.0 times as high as the predicted number of trades (~0.9k). The difference in underestimation is smaller for 2000-share trades as compared to 3000-share trades, but of the same nature. On a daily basis, the number of 2000-share trades actually executed (~83.7k) is 4.6 times as high as the predicted number of trades (~18.0k). In contrast, the number of 3000-share trades actually executed (~26.2k) is only 4.1 times as high as the predicted number of

Table 1
Trade frequency residuals.

Next Lower		Prominent Number		Next Higher		T-statistic for H_0: $\mu_l - \mu_p = 0$	T-statistic for H_0: $\mu_p - \mu_h = 0$
Trade size	Mean residual (μ_l)	Trade size	Mean residual (μ_p)	Trade size	Mean residual (μ_h)		
100	1.2078 (0.0040)	200	−0.0827 (0.0018)	300	−0.4145 (0.0019)	341.69	131.51
400	−0.4653 (0.0024)	500	0.0394 (0.0032)	600	−0.5772 (0.0029)	−155.77	149.09
900	−0.3058 (0.0045)	1000	1.0630 (0.0046)	1100	−0.5831 (0.0060)	−231.07	220.70
1000	1.0630 (0.0046)	2000	1.5397 (0.0075)	3000	1.4306 (0.0114)	−58.59	8.39
4000	1.2979 (0.0164)	5000	2.5183 (0.0132)	6000	1.1433 (0.0241)	−55.07	50.58
9000	0.8483 (0.0318)	10,000	2.6433 (0.0278)	11,000	−0.4400 (0.0073)	−45.21	97.01

Note: This table contains summary statistics for the daily residuals from non-parametric regressions of the logarithm of the proportion of trades in each size on trade size. The *t*-statistics corresponding to the null hypothesis that the mean residuals for the "Next Lower" and "Prominent Number" sizes are different are in the second to last column. Similarly, those corresponding to the null hypothesis that the mean residuals for the "Prominent Number" and "Next Higher" sizes are different are in the last column. Standard errors are in parentheses below the mean residual (μ_l, μ_p, and μ_h). All *ps* < .01.

trades (~6.3k). These raw values help to illustrate in somewhat more intuitive terms the extent to which Prominent-Number clustering exceeds Round-Number clustering.

To be comprehensive, we also included the "2" versus "1" comparisons in the table, but both are Prominent Numbers so we did not have predictions about which residual should be larger. We observe that there is more clustering on 100-share trades than 200-share trades, $t = 342$, $p < .001$. The table also includes comparisons of the residual for 1000-share trades relative to those of 900- and 1100-share trades, but these are difficult to interpret. The first comparison (1000 vs. 900) confounds Prominence and different orders of magnitude; the second comparison (1000 vs. 1100) confounds Prominence and roundness. Comparisons offered for the 10,000-share trades should be interpreted with similar caution. They are consistent with the Prominence account, $|ts| > 45$, but unavoidably confounded.

Study 1 provides strong evidence for the first prediction from the Prominent-Number conjecture. Investors' decisions about how many shares to trade disproportionately cluster on the Prominent Numbers. In fact, there are 7 Prominent Numbers within the 100 round-lot quantities that investors could select from in the range we examined and yet 87% of the trades were of a Prominent size. In the SOM we describe an additional analysis that tests whether these results depend on investor sophistication, proxied by the amount of institutional ownership of a firm. Consistent with an accessibility account, non-sophisticated (i.e., non-institutional) investors seem to rely more heavily on the cognitive shortcut afforded by Prominent Numbers.

These results provide good evidence of Prominent-Number clustering. They are the first that we are aware of to formally document Prominent-Number clustering in real rather than hypothetical judgments (cf., Whynes et al., 2005), and in a way that definitively separates it from Round-Number clustering. Further, a communication-based explanation does not seem applicable here. However, one limitation of inferring process from the outcomes alone is that apparently coarse judgments will occasionally reflect the occurrence that a Prominent Number precisely matches the signal. For example, "5000" could be offered by a judge who has *4400* in mind but determines that "5000" is close enough (as an estimate for herself); but it could also be offered by a judge who has (exactly) *5000* in mind. Probabilistically, the latter should happen infrequently, but subsequent studies allow stronger inferences because they examine clustering as a function of judgment conditions. A key implication of the accessibility account is that Prominent-Number clustering should be more apparent when investors are rushing.

3. Study 2: Trade size clustering in a naturally rushed environment

Research in a variety of contexts demonstrates that judges rely more on highly accessible information when they are under time pressure than when they are not (De Dreu, 2003; Gilbert & Gill, 2000; Horton & Keysar, 1996; Kruglanski & Freund, 1983; Pratto & Bargh, 1991). The proposed accessibility-based account of open numerical judgment suggests that judges first consider the limited set of Prominent Numbers and then, if able and willing to invest more effort, refine from there. It follows that judges should be more likely to stop early—reflecting stronger clustering on the Prominent Numbers—when they have to decide quickly.

3.1. Method

To examine open numerical judgments in a rushed, real-world decision-making environment, we examined a sample of trades that immediately followed Federal Reserve Open Market Committee (FOMC) statement releases. These releases occur during the trading day and tend to move markets, vastly increasing the pressure to make quick decisions. In contrast, most other market-moving information like earnings announcements and unemployment statistics are released after the market closes, giving traders time to reflect on the data after-hours. FOMC releases also occur with some frequency allowing us to construct a relatively large set of observations. As a comparison, we examined all trades that occurred on the following day, when decisions could once again be made relatively more deliberately. This is not a true experiment, so other factors (e.g., average investor sophistication) could potentially be varying concurrently. However, it provides a fairly well-controlled quasi-experimental context.

We identified all FOMC statement releases in the period from January 2004 to December 2011. There were 67 such releases. The statement is released at 2 p.m. on the last day of the FOMC's meeting. We examined all trades from 2 p.m. until 3 p.m. on the statement release date and, as a control, all trades in the same one-hour period on the following day when there was no statement release. To test whether traders rely more on Prominent Numbers to make their trade-size decisions on statement-release days than other days, we conducted a series of difference-in-difference tests. Specifically, we tested if the difference between the frequency of Prominent-Number sized trades and the frequency of the closest Round-Number sized trades is bigger on statement-release days than on the following day. For example, is the difference between 500- and 400-share trades bigger on statement-release days than on the following day? For simplicity, we used the observed frequencies rather than non-parametric residuals in this analysis because the expected frequencies would "drop out" in the difference-in-difference.

3.2. Results and discussion

Fig. 2 provides a simplified version of the results, illustrating that there are more trades of size 200; 500; 1000; 2000; 5000; and 10,000 on statement-release days than on the following days. Table 2 displays

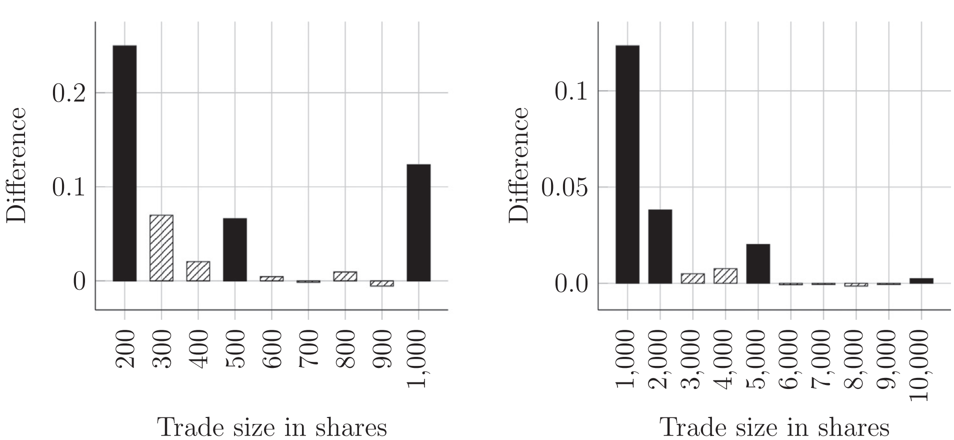

Fig. 2. FOMC frequency difference, release day minus following day. Note: Distribution of the difference in trade size frequency from 2 to 3 p.m. following the FOMC statement release and the same hour the following day. Prominent-Number sizes are shown in solid black, Non-Prominent sizes are shaded. The data are shown in two plots using different y-axis scales for small and large trade sizes. The data come from 67 statement release days between January 2004 and December 2011.

Table 2
Differences in trade frequency by Federal Reserve OMC statement release date.

Trade size	Trade frequency		Diff in diff ($t - c$)	t-statistic	p-value
	Statement release date (t)	Following day (c)			
200 (f_p)	12.486	12.236			
300 (f_n)	5.672	5.603			
$f_p - f_n$	6.813	6.633	0.180	3.76	< 0.001
500 (f_p)	3.692	3.626			
400 (f_n)	3.467	3.447			
$f_p - f_n$	0.225	0.180	0.046	1.53	0.065
500 (f_p)	3.692	3.626			
600 (f_n)	1.382	1.377			
$f_p - f_n$	2.311	2.249	0.061	2.11	0.019
1000 (f_p)	2.331	2.208			
900 (f_n)	0.700	0.705			
$f_p - f_n$	1.631	1.503	0.129	4.40	< 0.001
2000 (f_p)	0.546	0.508			
3000 (f_n)	0.175	0.170			
$f_p - f_n$	0.372	0.339	0.033	2.98	0.002
5000 (f_p)	0.198	0.178			
4000 (f_n)	0.085	0.078			
$f_p - f_n$	0.113	0.101	0.013	1.76	0.041
5000 (f_p)	0.198	0.178			
6000 (f_n)	0.021	0.022			
$f_p - f_n$	0.177	0.157	0.021	3.19	< 0.001
10,000 (f_p)	0.063	0.061			
9000 (f_n)	0.008	0.009			
$f_p - f_n$	0.055	0.052	0.003	1.08	0.141

Note: This table compares the frequency of trades of different sizes from 2 to 3 p.m. on days of Federal Reserve Open Market Committee (FOMC) statement releases (the treatment group, t) and the corresponding time period during the following day (the control group, c). There are 67 statement release days between January 2004 and December 2011. The first number in each test is the frequency of trades where the trade size is a Prominent Number (f_p), and the second number is the frequency at a Non-Prominent neighbor with the same precision (f_n). The t-statistics and p-values are for the test that the difference-in-difference equals 0.

the full results of the difference-in-difference comparisons. Across the board, Prominent-Number clustering is more prevalent on statement-release days than on control days. For example, on both control days and statement release days, there are more 200-share trades than 300-share trades; but, critically, this difference is larger on statement-release days. It is similarly true across all Prominent Numbers as compared to their Round-Number neighbors. To test this hypothesis for 2000-share trades we did comparisons relative to 3000, the nearest Non-Prominent Round Number. Similarly, we compared 5000 to 4000 and 6000. Results are consistent with the hypothesis in all cases. In results not reported in the table, we also compared 2000-share trades to 1900- and 2100-share trades; and 5000- to 4900- and 5100-share trades. The results were consistent with the results in the table.

Changes in odds-ratios (ORs) can be helpful for comparing the effect of FOMC releases on Prominent-Number clustering within relatively small trades versus relatively large trades. For example, using the information in Table 2, one can calculate that on control days, the ratio of the odds of observing a 200-share trade relative to the odds of observing a 300-share trade is 2.35; and this OR increases slightly to 2.37 on FOMC days. Moving up one order of magnitude, where there are many fewer trades, the ratio of the odds of observing a 2000-share trade relative to the odds of observing a 3000-share trade on control days is 3.00; and this OR increases to 3.13 on FOMC days. Thus, in general, the effect of FOMC releases on Prominent-Number clustering is reliable but relatively small, not surprising given the variety of factors that likely affect trade-size decisions. We emphasize the value of the 200-versus-300 comparison and the 2000-versus-3000 comparison because they are particularly useful for demonstrating the specificity of the Prominent Numbers. The effect is not just about "wholes" and "halves" (Albers, 1997, 2001; Jansen & Pollmann, 2001).

Like in any "natural experiment," we should acknowledge the possibility of third-variable problems, but, with that said, these results appear to support our general proposal that judges rely more on Prominent Numbers when they are unable or unwilling to invest the cognitive effort in refining their judgments. As in Study 1, there are two main clues that this is unlikely to reflect a communication-based phenomenon. First, in both studies, we directly benchmarked the Prominent Numbers against adjacent Round Numbers, which we assume to be equally grainy but less accessible, suggesting that the key difference is unlikely to be graininess, per se.

Second, in both studies, it seems unlikely that traders would have incentive to choose numbers to communicate their uncertainty. Especially in the rushed conditions on FOMC days, they may well have felt too uncertain to consistently refine their decisions beyond the highly-accessible Prominent Numbers, but it is unlikely that they would have selected a Prominent Number (over a finer number) specifically to communicate that uncertainty externally. Despite the strengths of Study 2, it lacks the precision of a true experimental design. In Studies 3a and 3b, we moved to an online-lab setting that allowed us to randomly assign participants to make judgments under time pressure or not.

4. Studies 3a and 3b: Rushing increases Prominent-Number clustering

In studies 3a and 3b, we used an experimental design that randomly assigned participants to submit a series of open numerical judgments under different timing constraints. As in Study 2, we predicted that participants who provided their judgments under rushed conditions would rely on Prominent Numbers more so than would those who could take their time.

4.1. Method

Participants in both studies were MTurk workers who signed up to participate in a 3-minute judgment study for $0.20. In Study 3a, participants viewed photographs of three different outdoor renovation projects and estimated the cost of each project. In Study 3b, participants made three different kinds of judgments: a trivia judgment ("How many passengers depart from Chicago O'Hare International Airport on a typical summer day?"), a visual judgment (based on a slightly blurry photograph, "How many people are on [the pictured] party boat?"), and a cost estimation ("How much did it cost to install [the pictured] inground pool?"). In the slow condition of both studies, instructions asked participants to "Please think carefully and try hard to give your best estimate" and to take "as much time as you need." A hidden timer on each page was set so participants could not submit their response to each question for at least 20 s. In the rushed condition of both studies, instructions asked participants to "Please give your best estimate" and informed them that they would have to answer "within 10 seconds." This condition included a visible 10 s countdown clock. In both studies, we included a 2 s grace period between the end of the countdown clock and the program's next action to allow participants to finish keying in their responses. In Study 3a, the survey software would not advance to the next question without a response, so if the clock timed out, it restarted after the 12 s. In Study 3b, the survey automatically advanced after the 12 s and non-responses were recorded as blank. The dependent variable was the proportion of participants' three judgments that utilized a Prominent Number.

The judgments in Study 3a were preceded by a three-item scale measuring interest in the judgment domain (all on 4-point scales, e.g., "Are you interested in home design?" with responses from 0 = *not at all interested* to 3 = *very interested*; α = .82) and followed by a single-item manipulation check ("How thoughtful were you able to be about your cost estimates?" from 0 = *Not at all thoughtful* to 4 = *Extremely thoughtful*). There were no other questions in either study. Full materials are available online. In Study 3a, we predetermined a sample size of 200 complete responses. Aiming for additional power, we predetermined a sample size of 400 in Study 3b.

4.2. Results and discussion

4.2.1. Study 3a

Two participants (both in the rushed condition) did not complete the study and were excluded from analysis. One participant who did complete the study provided an invalid (non-numerical) response for one of the estimation items and was also excluded, leaving a final valid sample of $N = 199$. The advertisement indicated that the study was about landscape design projects and, as expected, attracted a sample with high interest in the topic ($M = 1.59$ out of 3, $SD = 0.70$). Interest did not differ between conditions, $t < 1$. Supporting the apparent effectiveness of the manipulation, participants in the rushed condition reported that they were not able to be as thoughtful ($M = 2.48$, $SD = 1.00$) as those in the slow condition ($M = 3.28$, $SD = 0.59$), $t(157.8) = 6.81$, $p < .001$ (*df* adjusted for unequal variance).

Though Prominent Numbers represent less than 0.02% of the numbers between 0 and the maximum provided estimate of 100,000; they account for 29.5% of all estimates provided. To conduct our key analysis, we coded whether each judgment was Prominent (*no* = 0, *yes* = 1) and averaged those values to get a proportion of Prominent-Number judgments. With three judgments, this measure could take one of four values: 0.00, 0.33, 0.67, or 1.00. Consistent with our prediction, participants in the rushed condition used Prominent Numbers more often ($M = 0.35$, $SD = 0.30$) than did participants in the slow condition ($M = 0.25$, $SD = 0.28$), $t(197) = 2.43$, $p = .016$, 95% CI for the difference [0.02, 0.18]. Notably, participants in the rushed condition did not use Non-Prominent Round Numbers more ($M = 0.28$, $SD = 0.27$) than did participants in the slow condition ($M = 0.32$, $SD = 0.26$), $t(197) = -0.99$, $p > .25$, suggesting that the effect was specific to the Prominent Numbers. Examining participants' self-reports of how thoughtful they were able to be is also consistent with this conclusion. Self-reported thoughtfulness predicts fewer Prominent Numbers, $r = -.15$, $p = .031$, but has no relationship with the use of Non-Prominent Round Numbers, $r = 00$, $p > .98$, again providing more support for an accessibility-based account than for a communication-based account.

4.2.2. Study 3b

Twelve participants withdrew before completing the survey (5 in the slow condition, 3 in the rushed condition, and 4 before assignment to condition). MTurk logged 407 complete responses. We excluded 11 responses from participants in the rushed condition who did not successfully enter a numerical judgment within 10 s on at least one of the questions. The final sample is 204 participants in the slow condition and 192 in the rushed condition.

Though Prominent Numbers represent less than 0.001% of the numbers between 0 and the maximum provided estimate of 2 million, they represented 37.7% of all estimates provided. Replicating Study 3a, participants in the rushed condition used Prominent Numbers ($M = 0.41$, $SD = 0.31$) more than did those in the slow condition ($M = 0.35$, $SD = 0.30$), $t(394) = 2.05$, $p = .041$, 95% CI for the difference [.00, .12]. Participants in the rushed condition did not use Non-Prominent Round Numbers more ($M = 0.20$, $SD = 0.22$) than did those in the slow condition ($M = 0.20$, $SD = 0.24$), $t(394) < 1$, $p = .95$, again suggesting that time pressure specifically influenced the use of Prominent Numbers, not all Round Numbers.

Unexpectedly, the effect size was somewhat smaller in Study 3b (Hedges' $g_s = 0.20$) compared to Study 3a (Hedges' $g_s = 0.34$), perhaps resulting from the wider variety of judgments required in 3b. Given that both studies yield significant results and that these are the only two studies we have run using this paradigm, the result appears reliable. In a "mini meta-analysis" (calculated here and subsequently with metafor by Viechtbauer, 2010, for R, R Core Team, 2014), the standardized mean effect size was $Mg_s = 0.25$, $SE = 0.08$, $p = .003$, 95% CI [.08, .41]. Overall, Studies 3a and 3b support our prediction that forcing people to rush increases their reliance on Prominent Numbers.

While the causal effects support our account of how people employ Prominent Numbers, it is equally interesting to note the relatively small effects of forced rushing. These small effects may speak to the robustness of the overall tendency to use Prominent Numbers: It is apparently hard, even when forcing people to slow down, to push them off of the Prominent Numbers.

In contrast to the judgment context examined in Study 2, the contexts in Studies 3a and 3b are more open to accuracy—specificity tradeoffs (Yaniv & Foster, 1995). That is, we must acknowledge here that rushed respondents could plausibly have chosen Prominent Numbers versus finer numbers to convey a wider plausible range around their true estimate. If this mechanism was driving the phenomenon, though, it seems unlikely that the increased share of responses would have gone almost exclusively to the subset of Round Numbers that happen to be Prominent. In fact, the time pressure manipulation had virtually no effect on usage of the Non-Prominent Round Numbers. We would not necessarily even expect an effect on the Non-Prominent Round Numbers to be significant on its own, because increases in the Prominent Numbers would be part of the same effect, but there is precisely zero additional increase in the other Round Numbers, or, if anything, a small decrease, $Mg_s = -0.11$ ($SE = 0.08$), $p = .19$, 95%CI [−0.27, 0.05]. As throughout, we cannot definitively rule out that the Prominent Numbers might be even coarser than the Round Numbers; but the Round Numbers are coarser than all the other numbers and yet get used no more often under time pressure. On the whole then, these results seem to favor an accessibility-based account over a communication-based account.

While a number of studies have demonstrated stable (cross-cultural, cross-linguistic) regularities of number-word frequency (Dehaene & Mehler, 1992; Jansen & Pollmann, 2001), we believe Studies 3a and 3b, along with Study 2, are the first to explain some situational variance within that stability. Both are consistent with our proposal that additional cognitive effort decreases the likelihood of using a Prominent Number. Seeking convergent validity, the next set of studies moved to another manipulation, cognitive load, which should also increase reliance on highly accessible information.

5. Studies 4a–4c: Cognitive load increases Prominent-Number clustering

Research from a variety of judgment domains converges on the notion that people are more likely to accept whatever fast, initial, default judgments come to mind when they are under a high cognitive load, which stops them from executing slower, more deliberate correction or refinement processes (e.g., Epley & Gilovich, 2006; Gilbert, 2002; Gilbert & Gill, 2000; Kruger, 1999). For example, under cognitive load, people accept the veracity of statements more often (Gilbert, 1991); they are more likely to apply activated stereotypes (Gilbert & Hixon, 1991); they rely more on dispositional information, correcting less for situational information (Gilbert, Pelham, & Krull, 1988); they adjust away from self-generated anchors less (Epley & Gilovich, 2006); and they rely relatively more on their own perspective, engaging their theory of mind to understand others' perspective less (Lin, Keysar, & Epley, 2010). Based on these findings, and following the logic of Studies 3a and 3b, our accessibility account of Prominent-Number clustering predicts that people will use Prominent Numbers more often when they make judgments under high (versus low) cognitive load. Furthermore, given that cognitive load decreases people's ability to appreciate others' perspectives (Davis, Conklin, Smith, & Luce, 1996; Lin et al., 2010), it seems less likely that an increase in Prominent-Number usage could be explained by a concern for others' interpretations of the estimates.

5.1. Method

We conducted a series of three experiments to assess whether cognitive load affects Prominent-Number usage. The basic design of all three experiments is the same. We manipulated cognitive load in a within-subjects fashion, asking participants to complete one block of three numerical judgments under higher cognitive load and one block of three numerical judgments under lower cognitive load. Within each experiment, judgment items were completely randomized and block order was counterbalanced.

We opted not to use challenging mental rehearsal tasks, the most common cognitive-load manipulation, because we needed to run the studies online and wanted to minimize the role of cheating (by, e.g., writing down the letter-string). Instead, we made participants cognitively busy by asking them to execute a series of head movements while making their judgments. It is still possible that some participants falsely reported completing the head movements, but we took a number of steps to minimize this concern. First and foremost, we notified participants in advance about the nature of the upcoming task, trying to cast it as an interesting and fun alternative to the monotony of typical online studies. Specifically, the first screen in each study said, "Okay, so we're not going to lie: This is kind of a funny study……. We are trying to standardize body language while people answer some questions. So we are going to ask you to do some head movements while you read and respond." The instructions went on to provide some more detail and then asked, "Are you willing to follow the instructions? If not, please say so now, so we can both move on with our lives. We won't penalize you! And we'd still love for you to participate in some of our other studies. Thanks for your honesty!" Participants could then select, "Sounds strange, count me in" or "No thanks, maybe next time." Only participants who opted in were then directed to the formal consent document and then to the study.

Numerical-judgment presentation was similar to the "slow conditions" of Studies 3a and 3b. We ran three consecutive studies because the results were promising but inconclusive in each case. For each subsequent test, we attempted to increase our power by increasing the sample size and by refining the procedure to potentially strengthen the effect (see SOM for details). In Study 4a, participants completed three renovation-cost estimates (similar to Study 3a). In the high-load block, they made these estimates while moving their head around in small circles (we told them: "focus on moving your chin"). In Study 4b, we increased the sample size and the difficulty of the load manipulation by asking participants to execute a different movement for each of the three judgments in the block (first move head in circles, then switch directions, then move in small squares). We also added a timed delay to force them to consider each judgment for at least 15 s before submitting. In Study 4c, we further increased the sample size and aimed to further strengthen the difference between conditions by adding variety to the types of judgments, including cost estimates, population estimates, and other general-knowledge type questions. We also removed the forced-delay and added a short break between blocks. We used Prolific to recruit participants for Study 4a and MTurk for Studies 4b and 4c.

5.2. Results and discussion

Here, we present a mini meta-analysis of the three studies, with individual metrics presented in Table 3. In correlated designs such as the current fully within-subjects experiment, different effect-size estimates can vary greatly (see Dunlap, Cortina, Vaslow, & Burke, 1996; Goh, Hall & Rosenthal, 2016; Lakens, 2013; Morris & DeShon, 2002), but in our case it was not a consequential decision because the respective correlations between our repeated measures were quite low, *r*s < .3. In our case, the differences were negligible, diverging only after the point of rounding. Nonetheless, we followed the recommendations of Lakens (2013) to use Hedges' g_{av}, which provides a standardized mean difference using the average standard deviation across the two measurement occasions, as the most appropriate choice among the statistics in the "Cohen's *d* family" (including common variants of Cohen's *d* and Hedges' *g*).

Table 3
Use of Prominent and Non-Prominent Numbers under cognitive load.

Study	*N*	Control *M* (*SD*)	Cognitive Load *M* (*SD*)	*r*	Paired *t*-statistic	*p*-value
Panel A: Percentage of Prominent Numbers						
4a	121	33.6 (29.3)	38.3 (30.0)	0.29	1.46	0.15
4b	267	26.2 (29.7)	29.8 (29.0)	0.29	1.69	0.09
4c	304	36.2 (30.1)	40.1 (31.2)	0.20	1.78	0.08
Panel B: Percentage of Non-Prominent Round Numbers						
4a	121	28.9 (26.5)	28.9 (27.2)	0.10	0.00	1.00
4b	267	24.8 (26.4)	26.5 (26.3)	0.18	0.79	0.43
4c	304	26.9 (26.2)	26.3 (24.9)	0.03	−0.27	0.79

Note: Non-Prominent Round Numbers have one significant digit and begin with 3, 4, 6, 7, 8, or 9. *r* refers to the correlation between the repeated measures in the within-subjects experiment.

The three effect sizes were: Study 4a ($g_{av} = 0.16$), Study 4b ($g_{av} = 0.12$), and Study 4c ($g_{av} = 0.13$). Using a fixed effects approach, the local meta-analysis of these three experiments indicates that the weighted average effect size was $Mg_{av} = 0.13$. In raw-mean change-scores, this translates to a weighted average of $M = 0.04$ ($SE = 0.01$), $p = .005$, 95% CI [.01, .07]. In summary, it is clear that the effect of cognitive load on Prominent-Number usage is very small, but reliably positive. Though small, it is notable how consistent the data were across all three of the studies, considering the wide variability in judgments; the likelihood of many inputs into the judgment process; and, most likely, significant variation in participants' fidelity in executing the manipulation itself.

Aiming to compare the effect of cognitive load on Prominent-Number usage to its effect on Round-Number usage more generally, we calculated the same effect sizes of cognitive load on use of the Non-Prominent Round Numbers. The three effect sizes for these equivalently-round, but Non-Prominent Numbers were: Study 4a ($g_{av} = 0.00$), Study 4b ($g_{av} = 0.06$), and Study 4c ($g_{av} = -0.02$). Using the same meta-analytic approach, the weighted average effect size was $Mg_{av} = 0.03$. In raw-mean change-scores, this translates to a weighted average of $M < 0.005$ ($SE = 0.01$), $p = 0.74$, 95%CI [−0.03, 0.02]. As in Studies 3a and 3b, it is important to note that this is not a completely independent analysis from the above because, as the share of Prominent responses increases, there will necessarily be fewer candidate responses in the sample that might change from precise to Round. Nonetheless, if cognitive load was, in a more general way, increasing the use of all Round Numbers, then we would expect at least some evidence of an increase in the Non-Prominent Rounds. Yet, consistent with an accessibility-based account, we found no hint of such an effect. Like time pressure, cognitive load appears to increase reliance on numbers that are highest in both coarseness and accessibility (i.e., the Prominent Numbers), not just those that are the highest in coarseness (i.e., the Round Numbers).

6. Study 5: Prominent-Number clustering and the plausible scanning range

The least amount of cognitive work a judge could do to execute an open numerical judgment in the fashion we have proposed would be to scan the Prominent Numbers within some relevant range and then terminate the judgment process by selecting one of those numbers. We refer to this as a "first-order approximation" in the current context. Even if every judge only put in the work for a first-order approximation, not all judgments would necessarily require the same amount of effort investment. Some judgments should prompt most people to consider relatively narrower ranges, whereas other judgments should require most people to consider relatively wider ranges. For example, if you ask a typical American adult to estimate the population of a major American city, like Chicago, she might intuitively assume that the major American cities are "in the millions" and limit her search to a range from, say, 1 million to 10 million. In contrast, if you ask that same person to estimate the population of Asia, the intuitive bounds on her search might be much wider, perhaps from the hundreds of millions to the tens of billions.[7] We would say that even executing a first-order approximation would require the investment of more effort in the second case than in the first. In the first case, the individual would have to scan only four Prominent Numbers (1mm, 2mm, 5mm, 10mm) to make the least-effortful judgment, whereas in the second case, the individual would have to scan nine Prominent Numbers (100mm, 200mm, 500mm, 1b, 2b, 5b, 10b, 20b, 50b) to make the least-effortful judgment.

In this study, we tested whether people are more likely to use Prominent Numbers when the investment requirements of the specific judgment are higher. What we mean by "investment requirements" is that some judgments compared to others may require judges to scan more (base-10) orders of magnitude, and thus a wider array of Prominent Numbers, to arrive at an appropriate value. Formally, we examine the range (operationalized as standard deviations) of the log of people's judgments. This is consistent with the idea of logarithmic mental representation of the number line (Banks & Coleman, 1981; Dehaene, 2001, 2003, 2007; Nieder & Miller, 2003; Piazza et al., 2004). Intuitively, it captures the idea that scanning a range "in the millions" requires consideration of the same number of first-order reference values as scanning a range "in the billions" (1mm, 2mm, 5mm, 10mm in the first case; 1b, 2b, 5b, 10b in the second case), but that scanning a range from "hundreds of millions to tens of billions" requires scanning a greater number of first-order reference values (100mm, 200mm, 500mm, 1b, 2b, 5b, 10b, 20b, 50b, 100b). It is also important to note that higher magnitude judgments do not necessarily involve a wider range. For example, most judges may assume that the population of Chicago is "in the millions," but have no idea whether the population of Palm Springs, California is "in the hundreds of thousands or the millions."

The hypothesis here is that, holding person-level effort constant, judgments that on average require people to scan a wider (versus narrower) logarithmic range of plausible values, will manifest greater Prominent-Number clustering. To test this, we conducted a correlational study that treated stimuli as the unit of analysis. We asked a sample of judges to make twenty-four different numerical estimates, representing a variety of domains and spanning a wide range of magnitudes. For each stimulus, we could then calculate what we refer to as the *plausible range* by looking at the participant-level variation of log-transformed judgments. Our prediction was that items with higher plausible ranges would generate greater percentages of Prominent-Number estimates. Thus, at the item level, we expected a positive correlation between plausible range and percentage of Prominent Numbers.

6.1. Method

We recruited MTurk workers for an 8-minute judgment study for $0.85. We posted 100 slots and received 90 complete and valid responses. (The one complete response that we excluded was from a respondent who clearly did not take the task seriously, offering single-digit estimates for every item.) Participants responded to 24 judgment items. Twelve items were general knowledge questions from classic anchoring research (Jacowitz & Kahneman, 1995; most verbatim, some with slight adjustments), and twelve items were original (including some items from Studies 3a and 3b).

Adding general knowledge questions to an online study meant that participants could potentially search online for the answers. To pre-empt this practice, initial instructions said, "Please give your best estimate. Your pay does not depend on the accuracy of your answers, but the quality of our science does depend on you trying your best. Please, do not try to Google the answer or consult other sources. (Besides, what's the fun in that?)" At the end, we asked participants to report, without penalty of losing payment, if they succumbed to the temptation of searching for any answers and no participant indicated doing so. Response ranges and accuracy rates suggest this is at worst an isolated problem.

Prompts for each question were consistent with the prompts in the slow conditions of Studies 3a and 3b, asking participants to "Please think carefully and try hard to give your best best estimate" and to "take as much time as you need." After the free-response estimation for each item, the survey advanced to a new page for a confidence question, which read "How do you feel about your response?" (using a slider scale, 0 = *not at all confident* to 10 = *extremely confident*; Welsh et al., 2011; also Jerez-Fernandez et al., 2014). Items appeared in completely randomized order.

To calculate the plausible-range value for each item, we first winsorized at 2% and 98% to protect from disproportionate influence of outliers, especially on the high end of the distribution. We then took the log transformation of each individual response and, finally, calculated the standard deviation of the log-estimates on an item-by-item basis (*SDLog*).

6.2. Results and discussion

To give some intuition for the plausible ranges, the narrowest plausible range emerged for the question, "What is the median household income (USD) in the state of New York?" After winsorizing, raw estimates ranged from $20,000 to $500,000, with 89% of responses represented by a 5-digit number (i.e., tens of thousands). The *SDLog* value was 0.18 and only 12.2% of responses were a Prominent Number. In contrast, the widest plausible range emerged for the question, "How many gallons of water total are in the Great Lakes (Superior, Huron, Michigan, Ontario, and Erie)?" After winsorizing, raw estimates ranged from 500 to $4 * 10^{15}$. The modal response was a 7-digit number (i.e., millions), but only 26% of responses were in this order of magnitude. At least 5% of the sample provided answers in, respectively, the thousands, tens of thousands, hundreds of thousands, tens of millions, hundreds of millions, billions, and hundreds of billions. The *SDLog* value was 2.60 and 58.9% of responses were a Prominent Number.

For our focal item-level analysis, we regressed the percentage of Prominent Numbers on the plausible range (represented by *SDLog*). Consistent with the prediction we derived based on an accessibility account, the plausible range was a significant positive predictor of Prominent-Number usage, $B = 0.12$, $t = 4.41$, $p < .001$, 95% CI [0.06, 0.18].[8] Subsequent analyses also indicated that this is not just an effect of larger numbers. We note first that plausible range in this sample of

[7] In fact, these are not mere hypotheticals: In our sample, 73% of responses to the Chicago question were in the 1–10 million range and 73% of responses to the Asia question were in the 100mm—99b range.

[8] We initially planned to include self-reported confidence in the model to address a communication-based interpretation in a different way, but acknowledge in hindsight that interpretation of this analysis is difficult because of conceptual and empirical overlap between the two measures. For full disclosure, we note that confidence was a significant negative predictor of Prominent-Number usage, $B = -0.05$, $t = -2.18$, $p = .041$, 95%CI [−0.11, −0.00], but in a model with plausible range, it was no longer a significant predictor, $B = -.01$, $t < 1$, while plausible range remained significant, $B = 0.11$, $t = 3.45$, $p = .002$, 95% CI [.044, .178]. This is consistent with an accessibility-based account, but because of the overlap does not distinguish between this account and others.

items was related to number magnitude (operationalized as the median of the log of the raw estimates), $B = 0.17$, $t = 3.98$, $p = .001$, 95%CI [0.08, 0.26]. With that said, when we regress Prominent-Number usage on plausible range and number magnitude, plausible range remains a significant predictor of Prominent-Number usage, $B = 0.15$, $t = 4.51$, $p < .001$, 95%CI [0.08, 0.23] and magnitude becomes non-significant, $B = -0.01$, $t = -1.59$, $p = .13$. Furthermore, plausible range uniquely predicts Prominent-Number usage. Regressing the percentage of Non-Prominent Round Numbers on the plausible range and number magnitude provides no evidence of a positive relationship, $B = -0.05$, $t = -1.91$, $p = 0.07$. If anything, people may be less likely to use the other Round Numbers as plausible range increases.

The results of Study 5 are consistent with the idea that people rely on Prominent Numbers more so when they are making judgments that require them to scan wider (versus narrower) sections of a logarithmic number line. This effect is specific to the Prominent Numbers and does not hold for the other (Non-Prominent) Round Numbers. To summarize, whether judges were scanning at higher or lower magnitudes, they were more likely to rely on a Prominent Number to the extent that they were "out to sea" on an estimate; that is, to the extent that their intuition could not home in on a relatively tighter range, and they were forced to consider large swaths of the number line for an answer.

7. General discussion

In high-stakes field data and online survey data, we observed that people rely heavily on the powers of ten, their doubles, and their halves when making open numerical judgments, and this cannot be explained by mere 'hypothetical bias' (Whynes et al., 2005). We also observed that rushed and cognitively busy judges relied more on the Prominent Numbers than did their unrushed or unburdened counterparts. (Study S3 in the SOM also provides correlational evidence that less-motivated MTurkers used Prominent Numbers more so than their more-motivated counterparts.) Thus, consistent with an accessibility-based model of open numerical judgments, it appears that Prominent-Number clustering increases when judges cannot or will not invest additional cognitive effort in refining their judgments (cf., in the anchoring domain, Epley & Gilovich, 2006; Lieder, Griffiths, Huys, & Goodman, 2017; Turner & Schley, 2016; Tversky & Kahneman, 1974).

Though we must remain open to the role of grainy representation and communication norms in the observed phenomena (Welsh et al., 2011; Yaniv & Foster, 1995), we believe the results provide converging support for the central role of chronic accessibility. First and foremost, we would argue that the purchasing decisions in Studies 1 and 2 cannot be interpreted as a communication tradeoff. Traders do not purchase "around 1000" shares of stock. Second, every source of variation that we exploited (through measurement or manipulation) showed clear discriminant validity in its relationship with the Prominent Numbers specifically rather than with the Round Numbers more generally. In the stock data (Studies 1 and 2), massive samples allowed us to compare frequencies of Prominent-Number-sized trades to those of adjacent Round-Number-sized trades. The results overwhelmingly demonstrated clustering at Prominent Numbers that surpassed the degree of clustering at Round Numbers. For example, we found more clustering on 200 than 300 and on 2000 than 3000. In analyses of original participant data (Studies 3–5), relatively smaller sample sizes forced us to use a cruder approach to comparing Prominence effects to Roundness effects, but provided converging results. In sum, we believe the current results make a compelling case that the Prominent Numbers have a representational advantage over the merely Round Numbers.

7.1. Open questions

One limitation of the work to this point is that we have not directly assessed the chronic accessibility construct. Rather, we have inferred it by manipulating or measuring conditions known to promote the use of accessible information. Unfortunately, the very nature of the construct—*chronic* rather than *temporary* accessibility—would not allow for a direct manipulation, except perhaps over a very long timeframe. And even if we could decrease Prominent-Number clustering by increasing context-based accessibility (e.g., examining distributions of large chicken-wing orders) or temporary accessibility (e.g., examining distributions after priming "30"), decreased Prominent-Number clustering would reflect a net effect rather than a direct change in chronic accessibility. Aside from a longitudinal experiment, the best approach to assessing variation in chronic accessibility might be to make cross-cultural comparisons. This too would be difficult in practice because most languages are dominated by the base-10 system (Dehaene, 2011), but careful studies might nonetheless be able to capitalize on slight variations within that system (e.g., Chinese is a perfect reflection of the decimal system, whereas English and French are more mixed) or on variations in the chronic accessibility of non-decimal numbers for people who regularly pursue different activities (e.g., grocers deal in duodecimal more than people in other professions).

Future work should also strive for a more continuous characterization of the accessibility dimension. To this point, we have taken a similar approach to the extant Round-Numbers research that focuses on a categorical distinction between Round Numbers and Non-Round Numbers, while assuming a more continuous underlying dimension of graininess or roundness (e.g., Mason, Lee, Wiley, & Ames, 2013; Pope & Simonsohn, 2011; cf., Janiszewski & Uy, 2008). Though we focused on a categorical distinction between the Prominent Numbers and Non-Prominent Numbers, we presume there is a more continuous underlying dimension of accessibility. Our digital map of Spain provides a good intuition. At first, judges are zoomed out and only the most major cities, Madrid and Barcelona, are visible. Zooming in one level restricts the range of what is seen, but brings smaller cities like Valencia and Seville into focus. In open numerical judgments, we cannot yet specify what numbers come after the Prominent Numbers on the accessibility dimension. If a judge chooses 500 over 200 and 1000, but decides to zoom in one level, what numbers come into focus next? Determining the function that describes decreasing accessibility in a continuous way, from the most-accessible (Prominent) numbers down the spectrum, will be critical for building a more complete understanding of open numerical judgment.

Many variations are possible. One variation that builds from Albers and Albers' seminal perspective (1983) suggests that a continuous dimension could be defined by the number of Prominent Numbers required to make up the signal. This idea is based on prominence theory's elegant mathematical property that all integers can be constructed as a sum of non-repeated Prominent Numbers with coefficient -1, 0, or $+1$ (e.g., $1400 = 1000 + (1 * 500) + (0 * 200) + (-1 * 100)$). Albers and Albers theorized that people literally construct every number in this fashion, moving from the initially chosen Prominent Number (e.g., 1000) by applying coefficient -1, 0, or $+1$ to each successively smaller Prominent Number (e.g., 500, 200, 100) until they reach an acceptable estimate.

In one possible version of this refinement process, a "unit" of cognitive effort would be required to zoom in for each successive step of considering numbers that are lower in prominence. For this illustration, we use the term "degree of prominence" to refer to the number of successively smaller Prominent Numbers needed in a sum with coefficients $+1/-1$ (or 0) to reach an particular integer. For example, to arrive at a signal of 340, depending on the plausible range, a judge might initially consider the ("first-degree") Prominent Numbers from, say, 10 to 2000 [10; 20; 50: 100; 200; 500; 1000; 2000]. If she did not want to invest additional cognitive resources in the judgment, she would respond with "200." If she did want to refine, she would "zoom in" on the range that brackets the signal, in this case 200–500, and also consider the numbers in that range that are adjusted by the next smallest Prominent Number, 100. In this context, the 2nd-degree Prominent Numbers would be [200, 300, 400, 500]. If satisfied at this stage, the judge would respond with "300." Otherwise, she would "zoom in" further on the range from 300 to 400 and also consider adjustments up to the next smallest Prominent Number, 50. In this context, the 3rd-degree Prominent Numbers would also become accessible [300, 350, 400]. If she wanted to refine beyond "350," she would consider the range of 4th-degree Prominent Numbers between 300 and 350, now adjusting by up to 20, [300, 320, 330, 350], at which point she would be indifferent between 330 and 350 and split the difference by producing "340." Again, we acknowledge that many variations are possible, but propose this as one example of a more continuous accessibility-based refinement model.

There are some hints in our data that the Prominent Numbers continue to play a role in the refinement process after the initial coarse estimate. For example, in the trading frequencies, 1500-share trades (the sum of two Prominent Numbers) occur significantly more often than 1400-share trades (the sum of three Prominent Numbers). Much more work is needed here, but this hints at a larger role for Prominent Numbers throughout the process. Elegant cognitive experiments will be needed to tease out the exact refinement process and we hope that one contribution of the current work will be to motivate such efforts going forward. We also hope that this work will prompt further consideration of whether Prominent Numbers play an important role in other judgment contexts (as in Brandstätter et al., 2006).

7.2. Implications

Even as ongoing work aims to characterize the full process of open numerical judgment, the basic clustering phenomenon may have important implications. From a theoretical perspective, this work underscores the importance of recognizing both graininess and accessibility as important properties of number representation. It is easy to confound them because of their high correlation in reality. The set of Prominent Numbers is by definition a subset of the Round(est) Numbers, making it difficult to know whether to attribute various Round-Number effects to coarseness or high accessibility. We suspect that the answer is *all of the above*, with some effects attributable to a little of each mechanism and others dominated by one or the other. For instance, we submit that clustering in stock decisions is almost exclusively based on accessibility because communicating a confidence interval is irrelevant in that context, but acknowledge that offers in a negotiation context may be a joint function of accessibility (perhaps especially under rushed conditions) and intent to communicate a coarse value.

Even as the bounds of these various effects are mapped and explained, there may be some practical benefit to having identified the phenomenon of Prominent-Number clustering in open numerical judgments. For example, knowledge about Prominent-Number clustering could potentially be employed as a forensic tool to detect data fabrication. Based on the expected frequency of Prominent Numbers (high in human-created data, low in naturally occurring distributions), one might be able to flag potentially fraudulent data sets for further investigation (see Simonsohn, 2013, p.1884). Fraudulent survey data might have too few Prominent Numbers; fraudulent tax returns might have too many. Such observations alone would be insufficient, but could trigger further investigation. A more inspiring use might be to identify high-performing forecasters. One thing that sets "superforecasters" apart from others is their commitment to cognitive engagement in the estimation process (Mellers et al., 2015), a key negative predictor of Prominent-Number clustering. Future research might therefore examine whether less Prominent-Number usage is a reliable marker of a forecaster's ability.

In negotiations, an understanding of when people are likely to rely on accessibility in generating their first-offers could help to identify conditions that are more ripe for Round Number effects (Backus, Blake, & Tadelis, 2015; Mason et al., 2013; Pope, Pope, & Sydnor, 2015; Thomas, Simon, & Kadiyali, 2010). For example, rounder opening offers (e.g., $300) convey more willingness to negotiate than precise opening offers (e.g., $285 or $315; Mason et al., 2013); and it may be the case that first-movers open themselves to more aggressive counteroffers when they make decisions under rushed or distracting conditions. In some instances, what the speaker suggests may be largely attributable to the prominence of the number, whereas what the listener understands may be largely attributable to the roundness of the number. As research moves toward a more complete, and fully social, understanding of number communication in negotiations (see Loschelder, Friese, & Trötschel, 2017; Yan & Pena-Marin, 2017), it could be valuable to consider when Round Numbers are offered because of their roundness, per se, or because of their Prominence. The current findings suggest that the conditions that promote their use for each of these reasons would differ.

Finally, in consumer decision-making, an item's price relative to a Prominent-Number benchmark may be important. For instance, a variety of online tools allow buyers to set alerts that will notify them when a product goes below a certain price point. If buyers are biased to set these price-alert benchmarks on Prominent Numbers, then sellers might be advised to set prices accordingly. Beyond setting prices to take advantage of the "left digit effect" (Bizer & Schindler, 2005; Thomas & Morwitz, 2005), sellers in these situations might consider price points just below the Prominent Numbers to attract the most attention. For example, the decision to list a bedroom set on Craigslist at $499 rather than $500 might be more consequential than the decision to list it at $399 rather than $400 or $599 rather than $600. This may be particularly important for goods whose true value is ambiguous because these contexts would require potential buyers to scan a wider range of plausible numbers, thus increasing their likelihood of relying on a Prominent Number.

8. Conclusion

We have outlined and provided initial support for an accessibility-based shortcut that people may use to construct open numerical judgments. We suggest that judges begin by mentally scanning the chronically accessible, quasi-logarithmic scale defined by the Prominent Numbers—the tens, their doubles, and their halves. If they are able and willing, they may then invest additional cognitive effort in refining their judgments by considering decreasingly accessible numbers. By combining perspectives from numerical cognition, judgment, social interaction, and decision-making research, we hope this work provides a starting point for a comprehensive model of numerical judgment without anchors, and that it underscores the need to distinguish between multiple representational properties of numbers.

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Appendix A. Supplementary material

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