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Death of the Salesman but Not the Sales Force: How Interested Promotion Skews Scientific Valuation

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Whereas research has demonstrated how social cues appearing as disinterested social validation can skew valuation processes, interested promotion may be at least as important. This factor is examined here via the premature death of 720 elite life scientists. Especially when scientists are young and their articles have received little attention, their deaths stimulate a long-lasting, positive increase in citation rates, relative to trajectories for equivalent articles authored by counterfactual (i.e., still-living) scientists. These patterns seem largely explained by a spike in posthumous recognition efforts by the deceased scientists’ associates. The upshot is clear evidence of informational inefficiency, which derives from the challenges of absorbing the massive volume of research produced by the scientific community and from its ambivalence about the norm of disinterestedness.

INTRODUCTION

While it may seem obvious that buyers should not “judge a book by its cover,” sellers’ promotional efforts continue apace, in the apparently reasonable

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expectation that buyers will struggle and often fail to discount the seller’s biases. This struggle is especially salient in meritocratic domains, those governed and justified by strong norms enjoining participants to ignore social and physical cues and instead to assess products and producers purely on the basis of underlying quality. Consider science as the quintessential meritocratic domain, marked by widespread deference to the norms of “universalism” and “disinterestedness” (Merton 1979). Consider too that an important way of judging the health of a scientific field is whether it is informationally efficient: when scientific advances are made (according to the criteria of the field’s dominant paradigm, however imperfect it may be), are they recognized as such and does this recognition diffuse quickly? If some scientific papers owe their recognition not to the underlying quality of the work but to the fact that they benefited from more effective promotion, this would defy meritocratic norms and hinder informational efficiency.

At the limit, if science were just about who had access to the biggest promotional platform or used it most cleverly, public confidence in science would be misplaced. The question of whether such interested promotion of science limits the efficiency of scientific valuation can be better appreciated in the context of recent research on disinterested validation in meritocratic domains (see esp. Salganik, Dodds, and Watts 2006; Simcoe and Waguespack 2011; Azoulay, Stuart, and Wang 2014; van de Rijt 2019). Common to research on this type of social cue are three insights. First, given the widespread challenge of distinguishing higher-quality products and producers as well as the common need to coordinate on the basis of quality (Correll et al. 2017), third parties naturally emerge in meritocratic domains to aggregate and publicize informed assessments of quality (Zuckerman 1999; Espeland and Sauder 2007). Second, even when these assessments are produced in a disinterested manner—for example, by expert panels (Simcoe and Waguespack 2011; Azoulay et al. 2014) or by anonymous peers (Salganik et al. 2006; van de Rijt 2019)—they can skew valuations to produce informational inefficiency. In particular, when recognition is bestowed on one product/producer before it is bestowed on an equivalent one, the former may benefit from a “Matthew effect,” whereby the initial validation skews subsequent sampling, evaluation, and investment patterns. Finally, such advantages can be empirically
identified via counterfactuals derived from situations in which the same evaluative standards are used but disinterested validation of some products is higher for reasons that are unrelated to quality. This can occur either because (i) an experimenter has subdivided a population into subpopulations, and public quality assessments of the very same products happen in a different sequence in each subpopulation (Salganik et al. 2006; van de Rijt 2019), or (ii) an agent can only validate the quality of a limited number of products, thus entailing that a subset of equivalent products will have the bad fortune of not being validated (Azoulay et al. 2014; Bol, de Vaan, and van de Rijt 2018). Overall, these studies have produced clear evidence of informational inefficiency, although it is hardly overwhelming in its magnitude.

But insofar as disinterested validation of these varieties is distinct from the types of efforts at interested promotion mentioned above, it is unclear whether the latter type of social cue might also skew valuation and produce unfair advantage. The norm of “disinterestedness” enjoins scientists and scientific institutions to sanction scientists for attempting to boost the value of their work for personal gain (Merton 1942, p. 124). Accordingly, self-citations are often eliminated when assessing scientific contributions, as they are thought to be biased. Yet given the overwhelming volume of scientific research that is produced and the career stakes involved in gaining recognition, it is hardly surprising that scientists may be seen promoting their work in a wide variety of ways—on their vitae, on their websites, at academic conferences, in the introductions to their papers, and so on.

Moreover, there is reason to think that such efforts at interested promotion can influence the reception of science despite widespread fealty to the norm of disinterestedness and efforts to enforce it. In short, it is often difficult and even undesirable for scientists to treat interested promotion as biased. In particular, those with the most interest in a given line of work are often regarded as the most knowledgeable and as having the greatest incentive to accurately assess its quality (Li 2017; Teplitskiy et al. 2018). After all, it is generally a worrying sign if producers are not willing to stand by their work. A related consideration is that scientific movements often require a critical mass of contributors to make progress; as such, it is quite natural for scientists to promote work as a way of enlisting additional hands on deck (Botelho 2018). Finally, even if it is reasonable to dismiss a scientist’s efforts at self-promotion as irremediably biased, it is more questionable whether one should dismiss efforts by the scientist’s colleagues on his behalf. The upshot is that interested promotion generally falls into a normative gray area, making it difficult and often inadvisable to discount for its influence.

One implication of these considerations is to provide another basis for the Matthew effect (Merton 1968), whereby effectiveness in the promotion of
scientific work is increasing in a scientist’s status. But it also suggests that we can gain distinctive insight into the efficiency of the scientific valuation process by identifying contingencies that affect the manner and degree to which scientific work is actively promoted. In particular, research on reputational entrepreneurship in political and cultural contexts suggests that the death of a “producer” (i.e., an artist, politician, or scientist) provides a unique window into how shifts in the opportunity structure for interested promotion can have a significant impact on how the producer’s work is valued.

This literature identifies two countervailing effects of a producer’s death on such opportunities: on the one hand, death prevents the producer from playing the role of “salesman” in publicizing and promoting himself and his products, but on the other hand, the producer’s death can influence how other parties play the role of a “sales force” in publicizing and promoting the producer’s work (Bromberg and Fine 2002, p. 1139). In some cases, the death of the producer appears to have a negative effect on his legacy by eliminating the salesman. For example, in accounting for why U.S. President Warren Harding is the “worst president of all time” (Holmes and Elder 1989), Fine (1996) notes that Harding was a reasonably popular and effective president during his lifetime; however, his early death in 1923 prevented him from defending his reputation in the wake of the Teapot Dome scandal, while his erstwhile supporters had every incentive to let him take the blame. Yet while the death of the producer can have a negative impact on his legacy, it can paradoxically have a positive effect insofar as it mobilizes a sales force composed of people who were positively influenced by the producer during her lifetime. Thus, Lang and Lang (1988) document how the sudden death of young etchers mobilized friends and family to commemorate the oeuvre of the deceased, thereby making it less likely that the artist would be forgotten by the next generation. Fine (1996) too contrasts Harding’s death with John F. Kennedy’s, showing that Kennedy’s supporters commemorated his life and work to such an extent that he became one of America’s most popular presidents after his death, despite a rather brief and controversial term as president.

What then is the impact of scientists’ deaths, especially the premature deaths of young scientists, on the valuation of those scientists’ work? If the scientific valuation process is highly efficient (in discounting any bias in efforts to promote science), then the death of a scientist should have no impact on the valuation of her work. But if indeed a given scientific community is hard-pressed to absorb the work produced by its members and to discount any bias in promotional activities, contingent shifts in promotional opportunities can make a difference by either reducing recognition for the scientist’s work (if what matters most is the scientist’s self-promotion efforts) or increasing recognition for her work (if promotional efforts by supporters make the bigger difference).
American Journal of Sociology

To preview our findings, our analysis of elite academic life scientists shows that a scientist’s death tends to provide a boost to her papers’ citation trajectories, and it does so by mobilizing scholars seeking to memorialize the deceased, thereby promoting her work and reputation posthumously. As a result, these scholars’ research enjoys greater recognition than that of still-living scientists. We also find that these effects appear to be long-lasting; for up to 10 years after their deaths (a relatively long time relative to the citation half-life of articles in this field), the authors’ work continues to be cited more than comparable work by scientists who had not yet died. The effect is not uniformly distributed. It is more pronounced for those who are most memorialized, and consistent with findings by Lang and Lang (1988), such memorialization is disproportionate when the death occurs at a relatively young age. Additionally, it is the scientist’s least-cited papers at the time of death that see the largest boost in posthumous citations. Taken together, these findings suggest that the promotional efforts of the sales force are effective in shifting valuations and that the effect occurs because of an attention shift in the context of limited capacity for attending to the massive amount of scientific output.

THEORY

You have no control:
Who lives
Who dies
Who tells your story?
—Lin-Manuel Miranda, *Hamilton*

Our article examines the impact of contingent shifts in the opportunity structure for promotion on the informational efficiency of scientific valuation. To clarify the theoretical issues at stake, it is useful to consider what has been accomplished by recent research that examines the effect of contingent shifts in social cues on meritocratic valuation. In short, this research, which has largely been described as testing the Matthew effect (Simcoe and Waguespack 2011; Azoulay et al. 2014) or cumulative advantage (Salganik et al. 2006; Salganik and Watts 2008), has demonstrated that disinterested validation can shape which products/producers are more highly valued (as measured by citations or downloads, in the cases above). However, it is unclear whether interested promotion can have a substantial impact and what specific mechanisms might be responsible. To the extent that the Mertonian norms of universalism and disinterestedness govern science, one would expect scientists and scientific institutions to discount such efforts (Merton 1942). Yet scientific communities may find it difficult and even inadvisable to completely dismiss such promotional efforts, given that they may be reliable signals of quality. This ambivalence may make
interested promotion an effective means of boosting valuations, both by the focal scientist and by his supporters.

Disinterested Validation

A key contribution of recent research is methodological, in that it has shown that the clearest way to demonstrate that social signals shape valuation is through the use of counterfactuals that are identical or observationally equivalent to the focal products/services but do not enjoy the same degree of social validation. For example, the Columbia MusicLab experiment induces alternative popularity trajectories for the very same song, depending on whether it is evaluated in one of several different “social” worlds (in which popularity information is visible, such that songs’ initial popularity influences their later popularity) or in an “asocial” world in which popularity information is not given (Salganik et al. 2006; Salganik and Watts 2008). Similarly, Azoulay and colleagues’ (2014) study of how the conferral of status on life scientists by a prestigious foundation (the Howard Hughes Medical Institute, or HHMI) affects the citation trajectories of the scientists’ previously published papers is based on the premise that near-equivalent scientists (not anointed by HHMI) and papers (as discussed below) may serve as counterfactuals.

It is important to appreciate what this literature has demonstrated to date and what its limitations are. First, this research is focused on informational efficiency rather than allocative efficiency (Stout 1995; Sethi 2010; Zucker-man 2012b). Put differently, this research focuses on whether a particular community assigns valuations in a consistent manner as specified by its dominant paradigm but does not address whether the dominant paradigm is in an objective sense “correct.” This is most obvious in the case of the MusicLab, as the key question is the extent to which exposure to popularity information alters users’ perceptions of what would meet their personal taste (Salganik et al. 2006, p. 854). The same question is also implicitly operative in Simcoe and Waguespack (2011) and Azoulay et al. (2014): although it is possible that the work of both the award winners and the counterfactual (i.e., still-living) scientists will eventually be dismissed as having little value (thus implying allocative inefficiency), this is a separate matter from the informational inefficiency implied when the work of the award winner is valued more highly than equivalent work by lower-status peers. Note that this focus on informational efficiency is consistent with the thrust of science studies since the 1970s (Bloor 1973; Latour and Woolgar 1979; Shapin 1982; Ziman 1983), which have assailed the epistemological premise that scientific valuations can achieve objectivity. Scientific valuation necessarily reflects contingent communal standards, and insofar as those standards are necessarily limited, allocative efficiency is unattainable. But
this begs the question of whether a community applies its standards (however limited) in a consistent way. That is the question of informational efficiency.

Second, each of these studies focuses on disinterested validation. In the case of the MusicLab, the implicit premise is that music fans are limited in their ability to sample the vast universe of songs, so they look to their peers—who are presumed to have similar tastes—to guide them. This guidance is disinterested because it comes as a by-product of these peers’ consumption behavior and because the anonymity of the setting ensures that no one has an interest in promoting one song or another. Note also that this guidance is meritocratic in that it is ostensibly based on “the satisfaction of quality standards that can be articulated independently of the options available” (Correll et al. 2017, p. 299). Research on the Matthew effect in science is similar in both these respects. For example, the procedures that govern appointments to coveted Howard Hughes Medical investigatorships are presumed to be both disinterested and meritocratic because of HHMI’s institutional mandate to support high-quality research and from the review process’s adherence to the norm of universalism.

Third, it is important to consider two notable differences in the mechanisms affecting the informational efficiency of science from those in cultural domains, especially as examined in experiments in which the participants are anonymous and thus indifferent to how their valuations appear to others (see Zuckerman 2012a): (i) the prospect of tangible rewards for scientific advances that are independent of the valuation of the academic community and (ii) career-based social pressures in science that make scientists sensitive to their colleagues’ opinions. The first point derives from the premise that science is not purely a matter of taste; as such, there are significant rewards available to the scientist who challenges the dominant paradigm and successfully develops or inspires a piece of technology whose value becomes undeniable even to initial skeptics (e.g., polymerase chain reaction, CRISPR gene editing, or angiogenesis inhibitors). The second point derives from the premise that scientists’ career outcomes are determined by their fellow scientists, and this can induce significant pressure to conform to the dominant paradigm (it can also induce pressure to differentiate from their colleagues as competitors; Zuckerman 2012a). Given these two countervailing effects, one that rewards scientists for challenging convention and the other for adhering to convention, it is unclear ex ante whether the effect of social signals on valuation should be stronger or weaker in science relative to cultural markets. It is instructive then that while the results of recent studies demonstrate that the Matthew effect is real, its magnitude seems relatively

2 Notably, if they discover that their peers have very different tastes than they do, they tend to reject their guidance, and the social influence effect wanes (Salganik and Watts 2008; van de Rijt 2019).
small (Azoulay et al. 2014), thus implying a relatively low level of informational inefficiency.

Interested Promotion

Yet while this research has made important progress in assessing how social signals affect valuation, its focus on disinterested validation is necessarily limiting. After all, many social signals are conveyed by interested parties, and they too may have a significant impact on valuation. In cultural markets, such efforts are so commonplace as to be obvious: although Billboard may rank songs by market share (the equivalent of the disinterested validation provided in the MusicLab), this in no way deters artists and music labels from promoting their work through the use of advertisements, radio and playlist spots, television appearances, and so on.³ The prevalence of such promotional efforts is important for present purposes because it implies that market participants do not think that the market is informationally efficient (see Zuckerman 1999, pp. 1430–31). Rather, given the vast number of options available and the search costs associated with sampling them, efforts to gain the attention of consumers seem necessary.⁴ And as documented by marketing scholars (Van den Bulte and Lilien 2001), these efforts can pay off, by raising consumer awareness of the focal product or producer along with consumers’ perceptions of quality. Although consumers are typically aware that such efforts are biased attempts to sway their consumption behavior, they may be quite effective nonetheless.

But it is an open question whether and to what extent interested promotion may shape social valuation in science, affecting the informational efficiency of a given domain and thus potentially allocative efficiency as well. Insofar as scientific communities are governed by the norm of disinterestedness (Merton 1942), we might expect promotional efforts to be limited. Yet the same conditions that provide an impetus for promotional efforts in other settings—very large number of options and significant search costs—apply in science as well. As such, and given competition for scarce jobs and resources, scientists have good reason to fear that their work will not be noticed, thereby leading them to act as “salesmen” in promoting their work. Such promotion does not stop with the focal scientist herself; scientists often promote the work of others they know and respect. Although such promotional efforts are often presented as being disinterested and they may be less

³ It is possible—if unlikely—that some of MusicLab’s participants had an interest in promoting the bands they favored. To the extent that this was the case, the social cues would be a mix of disinterested validation and interested promotion. The specific contribution of interested promotion efforts would remain unknown, however.

⁴ Tucker and Zhang (2011) show that disinterested validation is more influential when there is less information available ex ante about consumption options.
self-interested than those of the salesmen, efforts by friends and colleagues—whom we term “the sales force”—to promote another’s work are not disinterested to the same degree as an anonymous ranking system (such as the MusicLab) or a third-party award (such as the HHMI). In particular, there is no comparable mandate or commitment by the promoter to assess a range of potentially meritorious candidates. In addition, the promoter may benefit either from reciprocal arrangements or from the increased status of a shared field (Reschke, Azoulay, and Stuart 2018).

But does (interested) promotion of scientific work significantly shape scientific valuation, and if so, how? Note in this regard Merton’s claim regarding the norm of disinterestedness was not that scientists are more moral and therefore less likely to attempt to boost scientific efforts for personal gain; rather, he argued that the institutions of science would be able to check such actions and prevent them from being effective (Merton 1942). Thus, one reason to doubt that interested promotion has a substantial impact is that scientific communities employ various practices—from removing self-citations from citation counts to avoiding advisors and coauthors when requesting journal referees and tenure letters—that are meant to counteract bias.

Yet as noted above, this is just one side of the coin. As with conflicts of interest in other domains, scientists’ investment in a subfield or a particular line of work (their own or that of a colleague) actually has ambiguous implications.5 In particular, someone who is interested in a particular domain may favor that domain, but she may also be more knowledgeable about it and more concerned about vetting the quality in it. Thus, as Li (2017) shows in her study of scientists assessing grants at the National Institutes of Health (NIH), while scientists may be biased in their valuations of quality in a manner that disproportionately benefits themselves and their colleagues, these (interested) scientists are also most accurate in their assessments, as they know more about their own domain and are most concerned about its trajectory. Moreover, given that scientific movements often require the mobilization of many colleagues to embark on complementary research, a natural consequence is that scientists will advertise their work so as to facilitate such mobilization. Indeed, the failure to promote one’s work in this fashion could even be interpreted as a negative signal.

The larger implication is that it is ultimately unclear whether and how scientists should discount one another’s promotional efforts, as they may be unsure whether such efforts are poor signals of quality due to bias or strong signals of quality due to aligned incentives. As such, there is good reason to expect that interested promotion has a substantial impact on the informational

5 This debate is common in many other domains outside of science. For instance, there is a long-standing legal precedent for the common law requirement of “legal standing,” meaning that parties must have been adversely affected themselves before they can bring a lawsuit forward (see, e.g., Lujan v. Defenders of Wildlife, 504 U.S. 555 [1992]).
efficiency of scientific communities. In particular, the general implication is that scientific work that benefits from more effective promotional efforts is more highly valued than equivalent work that does not benefit from the same level and type of promotion. A further implication is that if for whatever reason, a work of science benefits from extra promotion that is ostensibly unbiased, it should have an even greater impact than work that receives the same level of promotion but is perceived as biased.

Scientist’s Death as a Window into the Importance of Promotion

In order to assess these implications, we examine contingent shifts in opportunities for promoting science occasioned by the premature death of scientists. Past research has demonstrated that a scientist’s death can be effectively used to study a given scientist’s impact on the production of science (Azoulay, Graff Zivin, and Wang 2010; Oettl 2012; Azoulay, Fons-Rosen, and Graff Zivin 2019). And as discussed above, research on reputational entrepreneurship in cultural and political domains suggests that we can make progress on the larger question of the impact of interested promotion on the efficiency of scientific valuation by examining how appreciation for a scientist’s published work changes as a result of his death. Since the quality of such work (which was published in the past) is obviously unaffected by the death of its author, it should have no impact on how it is valued, as measured by the trajectory of citations to that paper. More specifically, to the extent that promotional efforts are biased and the scientific community successfully discounts for such biases, any effect of changes in promotional efforts due to the death should be negligible.

We have noted, however, why it is unlikely that such biases are fully discounted. And the literature on reputational entrepreneurship in cultural and political domains implies two pathways by which the death of a producer can affect how his work is valued based on how the death affects promotional activity. One possibility, as reflected in Fine’s (1996) study of Warren Harding discussed above, is that the valuation of scientific works will fall after the author’s death. Scientists who believe their research is undervalued by the community may seek to raise awareness of it through press releases, teaching graduate courses, presenting at conferences, and so on. This implies that at any given point in time, the level of citations a paper

\[ \text{Citations are necessarily a measure of attention (Merton 1988) but an imperfect measure of communal valuation given that some citations are negative. However, recent research (Catalini, Lacetera, and Oettl 2015) on a subfield (immunology) within the larger domain studied here finds that only 2.4% of the total citations have a negative valence. A more subtle issue is that citations may not reflect the citers’ personal assessment of quality but rather the assessment of quality she thinks coordinates well with journal referees and readers (see Correll et al. 2017). We will return to this issue in the discussion.}\]
receives is a function of the quality of the paper (according to the dominant paradigm) and the amount of “salesmanship” it has received. Thus, since the death of the scientist eliminates the latter factor, the number of citations should decline.

Second, as in the case of John F. Kennedy above, insofar as the death of a scientist leads scientists’ supporters to “memorialize” their deaths, it may generate an increase in the valuation of her work. Lang and Lang’s study of etchers provides intriguing evidence for how death can spur supporters to initiate celebrations of the artists’ life and work via “recognition events”—biographies, news articles, and exhibits of their life and oeuvre (1988, p. 94). To be sure, recognitions of a producer’s entire oeuvre often occur while she is still alive—a Festschrift is a common form of such recognition for scholars—but recognition events seem more common in the aftermath of the producer’s death. In Lang and Lang’s research, such events directed the etching field’s attention to the work of the deceased, thereby raising its perceived value to such an extent that memorialized etchers were remembered vastly beyond their living counterparts, even those who did superior work (pp. 93–94).

Importantly, Lang and Lang report that such memorialization was most impactful when the artist died at a young age. Lang and Lang’s (1988, pp. 93–94) example of Elizabeth Fyfe is emblematic:

Fyfe, who died in Switzerland in 1933, just after her thirty-fourth birthday after a long bout with tuberculosis, had been hailed by British critics as “one of the most original and accomplished young etchers.” That her name and her work, which amounted to just over 1,600 impressions, somehow survive, whereas those of others once equally or better known do not, has much to do with her premature death. Her teachers, her friends, her collectors, and other etchers rallied, while she was in the hospital, to organize an exhibition of her work, complete with catalog, and then used the proceeds from sales to help pay for the care she needed. Her dealer saw to it that her plates were printed when she could no longer do so herself and gave a full set of her prints to Fyfe’s sister. In this way, the many persons mobilized by the tragedy helped to preserve the work and, thereby, to sustain the memory of the artist.

An important factor noted here—the preservation of the artist’s otherwise perishable work—seems to apply to art but not to science. At the same time, science seems comparable to art and politics in that recognition events will be relatively rare for the young if they remain alive. Note further that young producers in a given domain tend to have more living supporters than those who die at an advanced age. Moreover, the deaths of those in the prime of their career are surprising and more likely to be experienced as tragic; as such, they may be more likely to mobilize a community that is keen to ensure that the scientist’s work not be forgotten. However well intentioned, such collective efforts at interested promotion have the potential to provide an ironic benefit to the dead scientist’s work via a boost in positive attention.
as compared with equivalent scientists who have the good fortune to remain alive.

Empirical Implications
Thus, the death of a scientist implies a contingent shift in opportunities for interested promotion. As such, it provides a lens through which we can examine how the informational efficiency of a scientific field is affected by interested promotion. If a given scientific field quickly and fully incorporates new advances (according to the criteria of its dominant paradigm), this would imply that the timing of the deaths of authors should not matter for how their research is valued, as measured by citation trajectories. But if such incorporation is incomplete and the field is not able to discount for any bias produced by interested promotion, such promotion—as elicited by scientists—can shift the level of appreciation for their work in one or both of two ways.

In particular, there are four possible ways that the valuation of a scientist’s work may be affected by her death. One possibility is that any shift in interested promotion has no impact, and scientific valuation is informationally efficient in this respect. The three other scenarios reflect some degree of informational inefficiency, whereby efforts at interested promotion are not fully discounted. Thus, a second possibility is that scientific valuations are significantly sustained by the efforts of the scientist himself; this would imply that the death of the salesman causes a decrease in citations to the scientist’s papers. A third possibility is that scientific valuations are significantly sustained by the efforts of a scientist’s supporters, and if the death of a scientist catalyzes the mobilization of this sales force, a boost in citations will ensue. Finally, it is possible that both channels have significant impact but cancel each other out. As long as either the underlying salesman or sales force effect can be identified, such an indeterminate outcome might still imply a significant degree of informational inefficiency in the field.

There is no strong theoretical basis for predicting which of these scenarios is most likely. At the same time, the first possibility seems unlikely. In general, informational efficiency in a domain requires effective tools for arbitrage (or “valuation opportunism”; see Zuckerman 2012b) whereby someone who recognizes a gap between quality and social valuation can profit from this gap even when others do not recognize it. But while such mechanisms do exist in various scientific fields (e.g., scientific contributions can be turned into technologies whose value is so apparent they cannot be denied), they tend to be relatively weak. More specifically, and as reviewed above, it seems unlikely that scientific fields are able to fully discount for biases that might be incorporated in efforts at interested promotion.
At the same time, it is not clear whether the mobilization of the sales force should overcome the absence of the salesman. On the one hand, the salesman has the most incentive to promote his own work and, therefore, is likely to do the most promoting. On the other hand, the efficacy of such efforts may be limited by the fact that the scientist is only one person, and his motives are transparently self-interested. As noted above, a key implication of our theoretical framework is that interested promotion should be more effective when those interests do not connote bias. Moreover, conditional on mobilization, the number of individuals in the sales force can potentially be much larger than a single scientist, and, as noted above, their efforts are unlikely to be viewed as entirely self-interested. These factors may be responsible for the evidence of the importance of posthumous “sales force” activity documented in the literature on reputational entrepreneurship (Lang and Lang 1988; Fine 2003). And yet we have noted that an important factor in such studies but absent from science is the role of the sales force in preserving a producer’s work. As such, we make no prediction as to which of the three other scenarios is most likely. Rather, our goal is to leverage our analysis to make progress in understanding whether interested promotion skews valuations and which channel is most important in doing so.

Our goal of learning about the relative importance of different channels for interested promotion is furthered by two more specific goals: (i) to assess the importance of key contingency factors that might alter the balance of the salesman and sales force effects and (ii) to examine whether the sales force effect indeed works via a spike in recognition events for dead versus still-living scientists. With respect to the first of these goals, four contextual factors seem especially important. First, as reviewed above, there is reason to think that the sales force effect will be especially strong for the young, with the key reason being that these scientists would have received much less recognition had they remained alive. Second, variation in the “engagement style” of the scientist may have an important impact on either the salesman or sales force effects. For example, scientists who tend to work with large research teams (coauthors, trainees) may be expected to have larger (posthumous) sales forces. Also of interest is whether scientists were highly self-promotional while they were alive. On the one hand, they may be dynamic personalities whose death catalyzes their colleagues to promote their deceased cohorts’ work in their stead. On the other hand, such scientists may be regarded as self-serving and be relatively ineffective at eliciting a posthumous sales force. Third, it will be instructive to examine how the shift in interested promotion affects scientists’ papers on the basis of their baseline citation level before their death. If a scientist’s most-cited papers earn the biggest citation boost from a scientist’s death, this will imply that a version of the Matthew effect is at work whereby interested promotion is most effective in combination with other forms of validation. But if a scientist’s
least-cited papers gain the most, this will imply a more narrow form of inefficiency, whereby a deceased scientist’s papers compete with another’s for scarce attention, with some losing out simply because of such scarcity. A spotlight on a scientist’s work will then increase the likelihood that overlooked work will now get its due (Tucker and Zhang 2011). Finally, we will examine not only changes in the number of citations to papers of the deceased versus the still living but also changes in who the citers are (collaborators vs. noncollaborators, in the same field vs. outsiders, working for the same institution or not, etc.).

With respect to the second goal, it will be important to examine not only the effect of death on citations to a scientist’s work but also the causes and effects of recognition events. Insofar as a scientist’s death indeed elicits a positive boost in the valuation of his papers, it may not be due to promotion by the sales force. For instance, it is possible that competitors of the scientist who were stingy in their citations before now become more generous. As such, it will be important to examine (i) whether indeed the death of a scientist elicits more recognition events than if he had remained alive and (ii) whether such recognition activity is responsible for any observed sales force effect on citations.

DATA AND EMPIRICAL DESIGN

The design of our empirical analysis unfolds in three separate steps. The first step is a causal analysis: we examine how the premature death of an eminent biomedical academic researcher changes the rate of citations to her work, compared to the work of other eminent researchers who do not die prematurely. The level of analysis for this step is an article/scientist pair, and the main challenge to be overcome is the building of a control group of articles that plausibly pin down the citation trajectories of the deceased scientists’ articles had they remained alive. In the second step, we examine whether recognition activity is greater for deceased scientists, controlling for a host of important correlates of individual recognition; the level of analysis is the individual scientist, and the key challenge is the measurement of the recognition process, which is highly variegated and would, at first blush, appear to defy efforts at quantitative reduction. The third and final step ties the earlier analyses together. We ask whether the recognition process is a plausible mechanism through which scientific work gets remembered in the long run. The main challenge is one of prediction: for each article, we must be able to forecast the citation trajectory that would have been observed if the scientist had remained alive, so as to isolate a net citation effect.

Death of the Salesman

Conversely, it is possible that evidence for the salesman effect is in fact evidence for diminished motivation to engage in strategic citation of the now-deceased scientist.
American Journal of Sociology

premium (or deficit) for this article. With these forecasts in hand, we can then examine whether variation in recognition intensity mediates the relationship between death and posthumous citations.

Below, we provide a detailed description of the process through which we assembled the data set used in the statistical analysis. We begin by describing the criteria used to select the sample of elite academics, with a particular focus on the timing and the manner of their deaths. The focus then shifts to the publications that deceased and still-living scientists authored during their lifetimes and how one might build a matched sample of publication/scientist pairs in which the citations received by articles authored by still-living scientists offer a plausible counterfactual to the citations that articles authored by deceased scientists would have received had they not died prematurely. Finally, we document how we measured the recognition process for each individual scientist. Throughout this description of the data, we outline how the construction of the sample addresses the empirical design challenges enumerated above.

Institutional Context

Our empirical setting is the academic life sciences. We focus on this domain for three reasons. The first is its sheer size: U.S. medical schools employ over 150,000 faculty members, and this figure underestimates the size of the labor market since it does not take into account scientists and engineers working at NIH, in nonprofit research organizations (such as the Salk Institute), for independent hospitals (such as the Cleveland Clinic), or within schools of arts and sciences (such as MIT; University of California, Berkeley; or Rockefeller University). Academic biomedical research also garners over 70% of all nondefense federal research and development dollars. The large size of the labor market is important for reasons of statistical power: our key source of variation is generated by the premature death of eminent scientists, and these events are relatively rare. Importantly, the members of this labor market share broadly similar norms, career goals, and incentives and operate within comparable institutional structures.

Second, scientific discoveries over the past half century have greatly expanded the knowledge frontier in the life sciences, and these advances have resulted in more specialization, as well as an increase in the size of collaborative teams (Wuchty, Jones, and Uzzi 2007). These trends help ensure that career shocks affect only relatively narrow swaths of the intellectual landscape. Were our research domain less balkanized across narrow subfields, it would be challenging for us to identify control articles or control scientists (Azoulay et al. 2019).

Third, and perhaps more pragmatically, our setting is blessed by an abundance of data sources. The careers of eminent, still-living life scientists are
extensively described in curriculum vitae, Who’s Who profiles, or laboratory websites. We combine these data with the free and publicly available bibliographic database PubMed, citation information from the Web of Science, and administrative records from the Faculty Roster of the AAMC and NIH’s Compound Grant Applicant File (CGAF). Together, these sources of information allow us to create an accurate longitudinal record of publications, citations, and funding for each scientist in the sample.

Our focus on the scientific elite is substantively justified in light of our goals. One would expect the articles of eminent scientists to be identified and evaluated immediately after their publication, relative to the articles authored by scientists of lesser repute. This should in turn lessen the relevance of interested promotion in influencing how science is valued. To some extent, this is testable since our metrics of eminence exhibit substantial heterogeneity even within our sample of eminent scientists. That said, this approach has limitations as well, which we discuss after presenting our findings.

Sample of Elite Academic Life Scientists
Following Azoulay et al. (2010, 2019), we begin by demarcating a set of 12,426 “elite” life scientists (roughly 5% of the entire relevant labor market) who are so classified if they satisfy at least one of the following criteria for cumulative scientific achievement: (i) highly funded scientists, (ii) highly cited scientists, (iii) top patenters, or (iv) members of the National Academy of Sciences (NAS) and the National Academy of Medicine. Because these four measures rely on achievements over the course of a scientist’s career, they will tend to select older scientists. To create more demographic balance, we add three additional measures that capture individuals with promise at the early and middle stages of their scientific careers (regardless of whether that success endures): (v) NIH Method to Extend Research in Time awardees, (vi) Howard Hughes Medical Investigators, and (vii) early career prize winners. Online appendix A (apps. A–F are available online) provides additional details regarding these seven metrics of “stardom.”

We trace back these scientists’ careers from the time they obtained their first position as independent investigators (typically after a postdoctoral fellowship) until 2006. We do so through a combination of curriculum vitae, NIH biosketches, Who’s Who profiles, accolades/obituaries in medical journals, NAS biographical memoirs, and Google searches. For each one of these individuals, we record employment history, degree held, date of degree, gender, and department affiliations, as well as a complete list of publications, patents, and NIH funding obtained in each year.8

8 Online app. B details the steps taken to ensure that the list of publications is complete and accurate, even in the case of stars with common last names.
The next step in the sample construction process is to select a subset of scientists from this overall pool whose premature death will “treat” their past output. First, we select scientists whose death occurs between 1969 and 2003.9 Second, we need to ensure that these scientists had not entered a preretirement phase of their career. This is trickier, because the timing of retirement is endogenous, and scientists who do not wish to retire can show great initiative in subverting rules surrounding mandatory retirement (which was legal in the United States until 1986). To overcome this challenge, we make full use of the narrative data contained in the dossiers we compiled for each scientist (deceased or not); we also examine publication output as well as funding received to remove from the sample those who either “meaningfully” retired or whose output shows sign of abating before their death or the end of the observation period.10

As a result of these steps, we identify 720 “treated” scientists (see table 1). The mean and median age at death is approximately 64, with the youngest scientist dying at age 33 and the oldest dying at age 91.11 We then investigate the cause of death in this sample to classify their deaths as being either “sudden” or “anticipated.” The main motivation here is to better identify when the sales force of those motivated to memorialize the scientist and his work would have become mobilized; insofar as the death is anticipated, this mobilization could begin before death. Distinguishing anticipated from sudden deaths is less difficult than it appears, since most obituaries typically are quite specific in this respect.12 To distinguish sudden from anticipated deaths, we use an arbitrary distinction between deaths that likely occurred with six months’ notice or less versus those that likely occurred with more than six months’ notice. In practice, this “sudden” category mostly comprises fatalities due to heart attacks, car accidents, and sudden-onset illnesses. Conversely, most “anticipated” deaths are from various forms of cancer or other long-term illnesses. In the deceased scientist sample, 330 (46%) scientists died suddenly, while 352 (49%) died from an anticipated illness.

9 An implication of this design choice is that even for the scientists who die “late” (e.g., in 2003), we will have at least three years of citation data to pin down how their passing changes the recognition of their work.

10 In previous work, one of us has verified that it is essentially impossible to predict death in a related sample using measures of lagged publication output (Azoulay et al. 2010).

11 How can one die at a very advanced age yet one’s passing still be deemed “premature”? Easily, as it turns out. Aubrey Gorbman (1914–2003), described in academic obituaries as the “father” of the field of comparative endocrinology, succumbed to Parkinson’s disease but still published two first-authored articles in the last year of his life.

12 In some instances, when the cause of death could not be ascertained from the obituaries, we contacted former collaborators individually to clarify the circumstances of the superstar’s passing. We were unable to ascertain the cause of death for 38 (5.28%) of the 720 deceased scientists. Some of these cases may have been suicides given the cultural taboo on publicizing suicide over much of this period.
Table 1 provides descriptive statistics for this sample (see online app. F for a complete list of these individuals, along with basic demographic information, institutional affiliation, and a brief description of their scientific domain). The overwhelming majority (91%) are men.\textsuperscript{13} Of note is the fact that even within this sample, substantial variation in status exists: whether one
measures eminence through publications, NIH funding, or citations (excluding those citations that accrue after the scientist has passed), the mean is always much higher than the median.

Difference-in-Differences Estimation Framework

The death shock that provides the essential lever for our research design occurs at the level of the individual scientist. Similarly, recognition and memorialization efforts typically focus not on particular articles but on the overall body of work of a scientist. And yet, our research design focuses on studying changes in citations to discrete academic publications in the wake of their authors’ passing, rather than changes in the flow of citations aggregated up to the scientist level of analysis.

We justify this crucial design choice as follows. Substantively, the norm of universalism emphasized by Merton as a hallmark of the scientific incentive system assumes that the identity of a scientific producer can be unbundled from her published works, at least in principle. The level of analysis in the first part of our study takes this distinction seriously. From an empirical standpoint, the scientist level of analysis is not well suited to the challenge of identifying the causal effect of death on the reception of an academic’s work. The content of every scientific contribution remains fixed after it is published, and only the way it is understood, celebrated, or denigrated can change over time. In contrast, the dynamics of the flow of citations received by an individual scientist reflects both increments of recognition accruing to past work as well as additional recognition enabled by new resources (e.g., funding, disciples) secured as a by-product of the reception of past work. The article level of analysis enables us to filter out the effect of the second source of variation, by anchoring the design around a very natural datum that determines unambiguously a “before” and an “after” period for each article: the timing of its author’s death.14

However, a simple difference between citations that accrue to a paper after, rather than before, the time of its author’s death is not enough to yield estimates with a plausibly causal interpretation of the effect of a scientist’s passing. This is because the memory of any article (or scientist) must eventually fade. Examine (in fig. 1A) the mean number of annual citations received by the 720 deceased scientists, both before and after the death. The

14 This approach is not new (Farys and Wolbring 2017). For instance, Murray and Stern (2007) ask how citations to articles shift once the underlying results appear in a patent; Azoulay et al. (2014) ask how the receipt of an accolade changes the citation trajectories of articles that appeared before the accolade was received; Azoulay, Graff Zivin, and Sampat (2012) investigate how the mix of local to nonlocal citations changes after a scientist moves to a geographically distant institution.
Fig. 1.—Citation life cycle for elite scientists. A, Total number of citations accrued per year by each of the 720 deceased scientists in the sample, within a window of ±40 years around their death. B, Number of citations accrued by each of the 8,326 still-living scientists who contribute at least one publication to the sample of control articles. Dashed vertical line indicates the average age at death for the treated sample, approximately 64 years old.
curve has an inverted U shape with a peak in the year before death, followed by an inexorable and steep decline, although it will take close to 40 years for the memory of any work by a deceased scientist to disappear from the scientific literature. Figure 1B produces a similar graph for the subset of still-living scientists who contribute articles to our control group (in a manner made precise below). In this case, we use their calendar birth age to display graphically the citation life cycle. The vertical dashed line age at 64 corresponds to the mean age at death in the deceased sample. There too, the flow of citations declines inexorably starting in a scientist’s late 50s, but that decline is much more gradual than what is observed for scientists who died prematurely. Therefore, the question for our study is not whether the recognition given to the work of deceased scientists will decrease after they die, as it surely will. Rather, the challenge is to assess this decline relative to the citation trajectory of articles whose recognition potential was similar at the time of the scientist’s passing. To do so, we need to construct a control group of articles that can plausibly capture this counterfactual.

**Matched Sample of Articles**

As in Azoulay et al. (2019), our approach is to identify control articles from the vast set of articles authored by elite scientists who did not die prematurely. For each article by a deceased scientist, we attempt to find at least one article by still-living scientists to pair it with. Although this step necessarily entails some degree of judgment, in order to yield valid comparisons, the matching procedure must meet a number of requirements. Notably, to contrast citation flows after the death shock, relative to before, we must be able to assign a counterfactual date of death to each control article as well as a counterfactual eminent scientist who could have died but did not. Pairing treated and control articles appropriately is therefore essential, since the control article will inherit certain characteristics from its matched treated article.

In particular, we require that each control article (i) be published contemporaneously with (and have a similar number of authors as) the article by a deceased scientist with which it is paired, (ii) be unrelated (in both an intellectual and a social sense) to the treated article with which it is paired, and (iii) have an author in last-authorship position who is a still-living elite scientist of approximately the same age as that of the deceased scientist on the article with which it is paired. The focus on the last-authorship position is a solution to the problem that modern science is a team sport, with steadily increasing rates of coauthorship over the past 40 years (Wuchty et al. 2007). Here, we are helped by a strong norm in biomedical research that invariably puts the principal investigator (PI) on a research project in last-authorship
position on any paper that results from the funding she or he was able to mobilize (Nagaoka and Owan 2014). In addition, it is important that the control group of articles as a whole be broadly similar to the treated group of articles, where similarity should be understood as reflecting average balance across key covariates at baseline. Although it is impossible to identify for each treated article a “fraternal twin” that matches it exactly on an exhaustive list of author and article characteristics, it is possible to select article controls in a way that will make the control group as a whole similar to the treated group in terms of expected impact and scientific “fruitfulness” at the time of the scientist’s death. Pragmatically, we specify a handful of covariates along which matched treated/control articles must resemble each other, and we implement a blocking procedure—described in detail in online appendix C—to identify all the articles among those published by still-living scientists that satisfy these criteria (so that each treated article can and typically does have more than one associated control article). Since judgment is required to choose the list of “blocking” covariates, online appendix C also provides two alternative matching schemes and probes the robustness of the core results when selecting one of these alternatives. Reassuringly, the main conclusions are robust to these variations. Our chosen approach yields a higher proportion of articles by deceased scientists with at least one match within the set of articles by still-living scientists. This has two benefits. First, the external validity of our findings is enhanced. Second, the larger sample size gives us more statistical power to detect heterogeneous effects by type of scientist or article.

**Treated/Control Article Pair: An Example**

Consider the paper “Isolation of ORC6” published in the journal *Science* in 1993 originating from the laboratory of Ira Herskowitz, an eminent University of California, San Francisco, geneticist who died in 2003 from pancreatic cancer. We match 34 publications to this article, also published in *Science* in 1993, on which a still-living star scientist occupies the last-authorship position. Figure 2 illustrates the matching with one of these articles, “Controlling Signal Transduction with Synthetic Ligands,” which came out of the laboratory of Gerald Crabtree, a Stanford pathologist who studied the role of chromatin in development and disease. By the end of 2002, the Crabtree...
Matching procedure to identify treatment and control articles. The two articles, which appeared in the journal *Science* in 1993, help illustrate the matching procedure (online app. C provides more details). Note that Ira Herskowitz and Gerald Crabtree are both in the last-authorship position. They obtained their highest degree in the same year. This procedure led the Li and Herskowitz article to be matched with 34 other articles in addition to the Spencer et al. article. Note that the articles are in very different subfields of the life sciences. Formally, the Li and Herskowitz article is not in the list of PubMed Related Citation Algorithm neighbors for the Spencer et al. article (and vice versa).
paper had garnered 214 citations, relatively close to the 218 citations that had accrued to the Li and Herskowitz paper—both articles belong to the top percentile of the 2002 citation distribution for the universe of papers published in 1993. Notice as well that Crabtree and Herskowitz were born in the same year (1946) and received their highest degree in the same year (1971). This is not happenstance, as the matching procedure requires that the career age (years since the highest degree was earned) of the treated and control elite scientists be no more than two years apart.

Yet there are still observable differences between this pair of articles and their authors. The two PIs do not match particularly closely on all metrics of cumulative achievement, for example. This is less of a concern than might appear at first blush, since as will be described below, we have found that imposing balance on article-level characteristics yields, as a fortunate by-product, approximate balance on scientist-level characteristics as well.

Two additional facts about this pair of articles are worth mentioning since they hold true more generally in the sample. Crabtree and Herskowitz never collaborated. Furthermore, these two papers belong to very different subfields of the life sciences. This is important insofar as a desirable feature of the control group is to be unaffected by the treatment event. By eliminating articles by collaborators as well as topically related articles from the list of eligible controls, we bolster the claim that the control articles can pin down a credible counterfactual citation trajectory.

Descriptive Statistics

The procedure described above yields a total of 454,599 papers authored by 8,326 control scientists, as well as 27,147 treated papers authored by the 720 deceased scientists. On average, there are 16.7 control articles for each treated article, highlighting the one-to-many feature of the matching procedure. Table 2 presents descriptive statistics for control and treated publications in the baseline year, that is, the year that immediately precedes the year of death for the deceased scientist. A number of the covariates are balanced between treated and control publications solely by virtue of the matching procedure—for instance, the year the article was written and the number of authors. However, covariate balance in the level of eminence at the time of (actual or counterfactual) death for treated and control scientists (measured

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16 Formally, the PubMed Related Citation Algorithm (PMRA), which will be described in more detail below, does not list one as being topically related to the other.

17 These 27,147 articles represent approximately 60% of the set of articles by treated scientists for which we attempted to find matches (i.e., original articles in journals indexed by PubMed and the Web of Science, in which the prematurely departed scientist occupies the last position on the authorship roster and published no later than the year before the year of death).
| Article:                        | Control Publications | Treated Publications |
|-------------------------------|----------------------|----------------------|
|                               | Mean     | Median | SD       | Min | Max | Mean     | Median | SD       | Min | Max |
| Age in year of death          | 4.48     | 5      | 2.57     | 0   | 9   | 4.48     | 5      | 2.57     | 0   | 9   |
| Year of publication           | 1976.64 | 1977   | 11.24    | 1950| 2002| 1976.64  | 1977   | 11.24    | 1950| 2002|
| No. of authors                | 3.19     | 3      | 1.58     | 1   | 15  | 3.20     | 3      | 1.56     | 1   | 13  |
| Citations at baseline         | 35.46    | 16     | 98.94    | 0   | 18,055 | 33.51    | 15     | 65.27    | 0   | 3,129|
| Citations by noncollaborators at baseline | 33.25  | 15     | 95.57    | 0   | 17,797 | 31.25    | 14     | 61.97    | 0   | 3,082|
| Citations by collaborators at baseline | 2.20  | 0      | 5.78     | 0   | 358  | 2.06     | 0      | 5.26     | 0   | 191  |
| Citations outside of field at baseline | 31.55  | 13     | 96.49    | 0   | 18,048 | 29.52    | 13     | 62.19    | 0   | 3,102|
| Citations within field at baseline | 3.91  | 2      | 6.22     | 0   | 162  | 3.79     | 2      | 6.11     | 0   | 138  |
| Citations from distant authors at baseline | 34.57  | 15     | 96.03    | 0   | 17,646 | 32.46    | 15     | 63.47    | 0   | 3,085|
| Citations from colocated authors at baseline | .89   | 0      | 4.00     | 0   | 410  | .85      | 0      | 2.91     | 0   | 122  |
| Investigator:                 |          |        |          |     |      |          |        |          |     |      |
| Year of birth                 | 1928.30  | 1928   | 10.44    | 1895| 1966 | 1927.53  | 1927   | 10.52    | 1893| 1960|
| Degree year                   | 1954.59  | 1954   | 10.76    | 1921| 1989 | 1954.32  | 1954   | 10.83    | 1920| 1988|
| Death year          | 1992.35 | 1994 | 8.32 | 1969 | 2003 | 1992.35 | 1994 | 8.32 | 1969 | 2003 |
|---------------------|---------|------|------|------|------|---------|------|------|------|------|
| No. of publications in matched sample | 51.74 | 39 | 48.58 | 1 | 355 | 86.64 | 69 | 72.28 | 1 | 414 |
| Cumulative no. of publications | 199 | 160 | 145 | 1 | 1,124 | 219 | 169 | 188 | 10 | 1,380 |
| Cumulative no. of citations | 13,586 | 9,359 | 14,318 | 17 | 188,430 | 13,799 | 9,895 | 12,264 | 77 | 76,231 |
| Cumulative amount of funding (×$1,000) | 24,196 | 15,678 | 28,322 | 0 | 408,427 | 27,435 | 14,949 | 47,940 | 0 | 329,969 |
| No. of trainees | 9 | 7 | 10 | 0 | 87 | 10 | 7 | 9 | 0 | 44 |
| No. of collaborators | 112 | 85 | 93 | 0 | 1,052 | 117 | 95 | 103 | 0 | 714 |

Note.—Sample consists of all of the publications for treated and control scientists that the matching procedure has culled from the universe of last-authored original publications by deceased and still-living scientists. The matching procedure is “one to many”: each treated article is matched with zero, one, or more control articles. The procedure matches 62% of eligible treated articles. The average number of control articles per treated article in the matched sample is 16.75 (median = 6, SD = 28.6, min = 1, max = 281). The descriptive statistics are weighted by the inverse number of controls in a matching strata. All time-varying covariates are measured in the year of the scientist’s death (or counterfactual year of death for the control scientist). The article-level citation counts correspond to the accumulated stock of citations up to the year of death. NIH funding amounts have been deflated by the biomedical R&D Producer Price Index (base year = 2007).
American Journal of Sociology

through NIH funding, number of articles published, or cumulative number of citations) was not guaranteed by the matching procedure.

Figure 3 examines differences in the shape of the distribution for citations received by treated and control articles, respectively, up to the baseline year. The two distributions exhibit very similar shape, including the far-left and the far-right tails. As highlighted below, balance in the stock of citations at baseline in the cross-sectional dimension of the data is not required for the validity of the empirical exercise. More important is the absence of differential trends in the flow of citations up until the time of treatment between the treated and control groups. An important step of the empirical analysis will be to verify, ex post, the absence of such trends before the death event.

Statistical Considerations

Our estimating equation relates the effect of a scientist’s death on citations in the following way:

\[
E(\text{cites}_it|X_{it}) = \exp[\beta_0 + \beta_1 \text{AFTER}_\text{DEATH}_{it} + \beta_2 \text{AFTER}_\text{DEATH}_{it} \times \text{TREAT}_i + f(\text{AGE}_{it}) + \delta_i + \gamma_i],
\]

where cites$_it$ is the number of citations paper $i$ receives in year $t$ (purged of self-citations), AFTER_DEATH denotes an indicator variable that switches to 1 in the year after the star scientist (treated or control) associated with $i$ passes away, TREAT is an indicator variable set to 1 if the scientist dies during the period, $f(\text{AGE}_{it})$ corresponds to a set of indicator variables for the age of article $i$ at time $t$ (measured as the number of years since the year of publication), the $\delta$’s stand for a full set of calendar year indicator variables, and the $\gamma$’s correspond to article fixed effects, consistent with our approach to analyze changes in the flow of citations within each article following the passing of an elite scientist.\(^{18}\)

We follow Jaravel, Petkova, and Bell (2018) in including in our specification an indicator for the timing of death that is common to treated and control articles (whose effect will be identified by the coefficient $\beta_1$) in addition to the effect of interest, an interaction between AFTER_DEATH and TREAT (whose effect will be identified by the coefficient $\beta_2$). The effects of these two variables are separately identified because (i) deaths are staggered across our observation period and (ii) control publications inherit a

\(^{18}\) To avoid confusion, we have suppressed any subscript for the scientist. This is without loss of generality, since each article is uniquely associated with a single scientist (i.e., there can only be one individual in last-authorship position for each article).
counterfactual date of death since they are uniquely associated with a treated publication through the matching procedure described earlier. The inclusion of the common term addresses the concern that age and calendar year fixed effects may not fully account for shifts in citation activity around the time of the scientist’s passing. If this is the case, AFTER_DEATH will capture the corresponding transitory dynamics, while AFTER_DEATH × TREAT will isolate the causal effect of interest. Empirically, we find that in some specifications, the common term has substantial explanatory power, although its inclusion does not radically alter the magnitude of the treatment effect.

Estimation.—The dependent variable of interest, citations accrued in each year (net of self-citations), is skewed and nonnegative. Specifically, 49.20% of the articles receive no citations in a given year, while 0.04% accumulate over 100. Following a long-standing tradition in the study of scientific and technical change, we present conditional quasi–maximum likelihood estimates based on the fixed effects Poisson model developed by Hausman, Hall, and Griliches (1984). Because the Poisson model is in the linear exponential family, the coefficient estimates remain consistent as long as the mean of the dependent variable is correctly specified (Gouriéroux, Monfort, and

![Figure 3](Death of the Salesman)

**Fig. 3.**—Baseline stock of citations. We compute the cumulative number of citations up to the baseline year, that is, the year that immediately precedes the year of death (or the counterfactual year of death) for the 27,147 publications by treated scientists and the 454,599 publications by control scientists. The histogram excludes articles with 250 or more accumulated citations in the year of death (approximately 0.5% of the sample).
Trognon 1984). We cluster the standard errors at the scientist level in the results presented below.

As discussed above, we pursue two empirical goals beyond testing for the overall effect of death on citation levels. One goal involves exploring four contextual factors. In addition to examining how the net effect varies depending on the relative youth of the scientist, we examine variables associated with three broad factors: (i) a paper’s impact history, (ii) a scientist’s engagement style, and (iii) the identity of citers.

**Paper impact history.**—The key consideration here is that papers may vary in their susceptibility to interested promotion on the basis of how much impact they have made up to the time of death (or counterfactual death). To get at this, we assign each article the percentile of the citation distribution to which it belongs, given its vintage. When computing these empirical distributions, we take into account both the year of death (citations that accrue after the year of death or counterfactual death are excluded) and the year of publication. This allows us to compare the citation impact of each article in the sample, regardless of the year in which it appeared and regardless of the time of treatment, relative to the article’s age. Using this information, for each scientist we create five distinct article subsamples: (1) the set of articles in the top 10% of impact at time of death, (2) the set of articles in the bottom 10% of impact at time of death, (3) the set of articles in the second and third quartile of the impact distribution at time of death, (4) the set of articles in the top 1% of impact at time of death in the PubMed universe, and (5) the set of articles published in a narrow window of three years before the time of death. Note that subsamples 1–3 use a relative benchmark to delineate a set of articles (e.g., every scientist in the data has a top 10% and a bottom 10%). The fourth subsample uses a universal benchmark, and it is possible for scientists in the data to contribute no articles to this subsample.

**Engagement style.**—The basic premise here is that the manner by which scientists engage with the scientific community (before death) may shape how their work is recognized (posthumously). We measure two aspects of such engagement style. The first reflects the “gregariousness” of the scientist, as reflected in the number of coauthors or trainees with whom he has worked. Arguably, we may expect such scientists to experience a more pronounced posthumous citation upsurge. The second reflects the scientist’s predilection for self-promotion. One view might be that self-promotional activities while alive “prime the pump” for the posthumous mobilization of his supporters. Conversely, it might be that the activities of the salesman and the sales force

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19 For example, revisiting the example presented on fig. 2, Ira Herskowitz’s *Science* publication belongs to the top percentile of the cumulative citation distribution for all articles published in 1993 and indexed jointly by PubMed and the Web of Science (only citations up to 2003, the year of death, are included in the computation). It is also ranked 10th among the 117 original articles he published before his death.
are substitutes, for example, because self-promoters are deemed unworthy of further glorification upon passing. Our proxy for self-promotion is a scientist’s rate of “gratuitous” self-citation, which we define as the proportion of all citations that are self-citations for which the cited paper is in a subfield different from that of the citing paper (with subfields corresponding to those defined by PMRA), in the entire portfolio of publications for a scientist in the predeath period.\(^20\)

**Citer identity.**—In order to better understand the activities of the sales force, characterizing the relationship between the citing authors and the cited is of interest. Specifically, are posthumous citations more likely to come from former collaborators or trainees? Are they more likely to originate from within the narrow subfield of the cited article or from outside that narrow subfield? Or are they more likely to be circumscribed in geographic space, for example, emerging from authors employed by the same institution as that of the deceased scientist? We parse all the citing-to-cited article pairs to distinguish between such relationships in social space, intellectual space, and geographic space.\(^21\) We then aggregate these data up to the article-year level to compute citation counts from related versus unrelated authors.

**Measuring Individual Recognition in Science**

Recall that the second step of our empirical analysis involves comparing recognition activity for deceased versus still-living scientists. Our approach leverages the existence of institutionalized occasions over the course of a scientist’s career in which her body of work is positively recognized. Perhaps most prominent among these include memorial events and obituaries written after death and Festschrifts or career awards (such as induction into the NAS or receipt of the Nobel Prize or Lasker Award) before death. In addition, professional journals routinely interview scholars to provide a perspective on the evolution of their fields or publish retrospective articles. The common thread across these “recognition events” is that they celebrate

\(^{20}\) We experimented with several variants of this measure, including defining self-promotion as the proportion of gratuitous self-cites, as opposed to the proportion of all cites. The results presented below were qualitatively unchanged.

\(^{21}\) Matching each author on citing and cited articles with the Faculty Roster of the AAMC allows us to distinguish between publications with and without former collaborators or trainees and with or without authors colocated with the focal elite scientist. Similarly, the use of the PMRA helps us distinguish between citations coming from within the same subfield, as opposed to outside the subfield. Importantly, this parsing can be implemented for the articles authored by both the treated and the placebo scientists, in a rigorously symmetric fashion. Finally, we distinguish between geographically proximate vs. distant citers using authors’ institutional affiliation obtained from the AAMC Faculty Roster and NIH’s CGAF database.
the scholar as an individual producer rather than narrowly shine a light on individual articles. Importantly, the rate of arrival of these events (if they occur at all) is not exogenous but rather reflects an investment on the part of fellow scientists. A cynic could be forgiven for thinking (probably not out loud) that many such events would go unrecorded unless they served the memorializers’ interest, in addition to the lofty and well-intentioned goal of enhancing or preserving the legacy or career of the individual being recognized.

Accordingly, we undertake a large-scale effort to collect articles recorded in academic journals that celebrate, recognize, or memorialize the scientists in our sample, whether they are deceased or still living. The challenge is to do so in a manner that is consistent over time and does not entail a built-in bias in favor of the deceased. To do so, we rely on PubMed, a publicly available bibliometric database curated by the Library of Medicine, which contains, as of the end of 2018, 29 million records for the biomedical research literature, life science journals, and online books. Helpfully, every publication indexed by PubMed is tagged by one or more of 80 distinct publication types, 10 among which could potentially denote a personal recognition event. Sifting through these articles in a systematic way, we build a data set of 5,850 distinct articles that pertain to one of the scientists in our database, deceased or still-living control. While there are more events overall in the control sample, the average number of events per scientist is much higher for the deceased than for the still-living scientists (1.74 vs. 0.52 on average).

In order to compare the intensity of recognition between prematurely deceased and still-living scientists, we leverage our research design. Recall that a by-product of the matching procedure at the article level is to generate a counterfactual year of death for each elite scientist whose articles match those of treated scientists. This counterfactual year of death provides a temporal anchor to compare recognition for the deceased as well as the living. A slight complication arises since the same scientist can serve as a control multiple times, for different treated scientists who passed away in different years between 1969 and 2003. As a result, there is typically more than one counterfactual year of death for each control scientist. To get around this problem, we simply select at random one of the possible counterfactual years of death for each living scientist. We then use a window of one year before until four years after the year of death (or counterfactual death) symmetrically for

22 Consider, e.g., Goldberg (2007). While the article highlights the impact of two articles in a specific subfield, it does so with a clear focus on the context that leads the investigator to develop a novel experimental paradigm to study visual perception in primates and features his picture prominently.

23 Online app. E provides additional detail on the identification of these events that involved a manual hand-coding effort to weed out false positives due to homonyms.
deceased and control scientists and sum the number of recognition events for each scientist within that window.

Figure 4A displays the histogram for the distribution of events, broken down by treatment status. The distribution of recognition is extremely skewed for deceased and still-living scientists, but recognition is a relatively rare event for the 8,326 control scientists: only 6% are recognized at least once, whereas 49% of the deceased are the subject of a recognition event. This simple comparison provides important validation for a key premise of our argument, which is that death is an exogenous shock that shifts opportunities for interested promotion.24

Predicting Long-Run Posthumous Citations

The third and last step of our analysis examines whether recognition efforts plausibly lie on the causal pathway linking the premature death of a scientist with his citation “afterlife.” To do so, we face the challenge that posthumous citations could be mechanically related to memorialization activities (e.g., the publication of a special volume dedicated to the work of the deceased, which necessarily includes citations to his work) and more broadly to the activities of the deceased’s sales force. To avoid the reflection problem entailed by correlating two variables driven by the same underlying process—the mobilization of the sales force—we must predict posthumous citation using information available before the death event exclusively.

A natural starting point might be to use the estimates from the causal model to generate predictions. However, the difference-in-differences modeling strategy, while well suited to the challenge of estimating the causal effect of premature death on citation trajectories, is not adapted to the task of predicting, at the article level, the future time path of citations.25 To generate article-level predictions, we begin by collapsing the data in the longitudinal dimension, such that for each article (treated or control) there are

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24 Given the sparsity of the recognition data—a vanishingly small number of still-living controls receive more than one event during the window—our empirical analysis at the scientist level will focus on the probability of being recognized (modeled with a logit specification), rather than the intensity of recognition. In online app. E, we present additional analyses of memorialization specifically for the sample of 720 scientists. In this smaller sample, there are enough events (especially after bringing in additional types of memorial events beyond those appearing in professional journals) to model the intensity of memorialization using count data models.

25 In fact, the conditional fixed effects Poisson estimator only allows us to characterize how a scientist’s death shifts the conditional mean of the flow of citation over time. It would be invalid to use the resulting estimates to compute a prediction for each article in the sample. Yet, it is the appropriate estimator for the causal analysis because it will generate consistent estimates under mild regularity assumptions (Wooldridge 1997).
Fig. 4.—Academic memory and recognition events. A, Histogram of the number of academic memory events for the sample of 720 deceased scientists and 8,326 still-living scientists, within a window of one year before/five years after the year of death (for deceased scientists) or counterfactual year of death (for deceased scientists). B, Dots correspond to coefficient estimates for the marginal effects in logit specifications modeling the probability of an academic memory/recognition event for a scientist, as in table 7. In addition to the list of covariates in column 7, we include age-by-treatment interaction effects whose coefficients are depicted. Bars correspond to 95% confidence intervals (calculated using robust SEs).
exactly two observations, one before the year of death or counterfactual
dead and one from the year of death onward.

We then construct a list of 728 predictive features, including the number
citations that accrued to the article in the predeath (or pre–counterfactual
death) period (log transformed), a female scientist indicator variable, year of
publication effects, type of degree effects, a full suite of indicator variables
for the scientists’ year of (possibly counterfactual) death, a series of indicator
variables for scientists’ highest degree graduation years, and 472 indicator
variables for each journal in which each article appeared. Using these fea-
tures, we perform a penalized Poisson regression with Lasso regularization
to generate predicted postdeath citation rates without overfitting the data.26

For each article, we compute the number of “excess” citations, that is, the
difference between actual posthumous citations received and the predicted
score. Panel B of figure D1 in the online appendix displays the histogram for
the distribution of this measure, which is skewed and takes on negative val-
ues (the median of the distribution is –4.6). In the article-level sample of ex-
tinct scientists, we can run simple ordinary least squares (OLS) speci-
fications in which excess citations are regressed on an indicator variable for
having a deceased last author, a nonlinear function of the intensity of rec-
ognition activities for each scientist, as well as a large vector X of control
variables (such as year of publication effects for each article, gender, highest
degree, cause of death, age at death, and year of death indicators):

$$\text{NegLog(excess_cites}_i) = \beta_0 + \beta_1 \text{DECEASED}_i + \sum_{k=1}^{3} \gamma_k \text{I}_{\text{events} = k}$$
$$+ \beta' X_i + \epsilon_i,$$

(2)

where $\text{NegLog}(x) = \log(x)$ if $x > 0$ and $-\log(-x)$ if $x < 0$ (Yeo and John-
son 2000). We are primarily interested in examining whether the correlation
between death and posthumous citations is mediated by recognition efforts.
If this were the case, the coefficient $\beta_1$ should decrease in magnitude or even
vanish once the intensity of recognition is controlled for in the specification
(by including the series of indicator variables, corresponding to three differ-
ent levels of recognition intensity, as right-hand-side covariates).

26 Online app. D provides more details, as well as sensitivity analyses, using a much more
parsimonious negative binomial model estimated by maximum likelihood, as well as a
high-dimensional fixed effects Poisson estimation routine (Correia, Guimarães, and Zyl-
kin 2019). The variant we selected, based on the plug-in formula for the Lasso (Belloni,
Chernozhukov, and Wei 2016), generates by far the best out-of-sample predictions (as as-
certained by the deviance residuals) but interestingly exhibits the smallest correlation
with actual posthumous citations.
RESULTS
The Effect of Premature Death on Citation Rates
Table 3 presents the main results for the first step of our analysis, and figure 5 provides corresponding event study graphs. These are created by estimating a specification in which the treatment effect is interacted with a set of indicator variables corresponding to a particular year relative to the scientist’s death and then graphing the effects and the 95% confidence interval around them (e.g., figs. 5A, 5B, and 5C correspond to table 3 cols. 1, 2, and 3, respectively).

The estimate in table 3, column 1, implies that the papers by deceased scientists receive a boost in citations after the scientist passes away, relative to the papers of still-living scientists, with an estimated magnitude of 7.4%. Figure 5A shows that this effect is long-lasting. After a pronounced upsurge in citation rates in the three to four years that immediately follow the death event, the magnitude of the effect tends to attenuate and is less precisely estimated, although only in figure 5C (corresponding to older stars) is there clear evidence of reversion to the pre-event mean of zero effect. Overall, it seems that however important a scientist is as the salesman for promoting his work, this pales in comparison to the promotional effect of the third-party sales force. More generally, we have clear evidence of a distortion in the informational efficiency of the scientific valuation process, whereby the death of a scientist seems to raise the valuation of a scientific paper by dint of the contingency of its lead author’s untimely demise.

The additional results in table 3 and figure 5 shed light on two issues discussed above: (i) whether the death was anticipated and how such anticipation might alter the strength of our conclusions and (ii) whether the effect is more pronounced when the death occurred at a young age. With regard to the first issue, it seems clear from figures 5A, 5B, 5C, and 5E that there is no discernible evidence of an effect in the years leading up to the death. The absence of differential citation trends between treated and control articles provides an important ex post validation of our identification strategy. In figure 5E (corresponding to the subsample of articles by treated scientists who died from an anticipated illness and their associated control articles), one can observe a positive and marginally significant increase in citations in the year before death. It seems that for anticipated deaths, news of the scientists’ terminal illness increases attention to the scientists’ work before

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*In these specifications, the AFTER_DEATH term that is common to treated and control publications is also interacted with a complete series of lags and leads relative to the year of death or counterfactual death.*
### TABLE 3
**Effect of Scientist’s Death on Citation Rates, by Age and Cause of Death**

|                      | All Causes of Death | Sudden Deaths | Anticipated Deaths |
|----------------------|---------------------|---------------|--------------------|
|                      | All Ages            | ≤65 at Death  | >65 at Death       | ≤65 at Death | >65 at Death |
| After death          | .07*                | .08*          | .07                | .10*         | .03          | .06          | .13*         |
|                      | (.03)               | (.03)         | (.06)              | (.04)        | (.08)        | (.04)        | (.08)        |
| No. of investigators | 9,038               | 8,567         | 4,500              | 7,524        | 3,533        | 6,749        | 3,568        |
| No. of source articles | 481,337            | 309,154       | 172,183            | 138,545      | 70,012       | 161,651      | 93,625       |
| No. of source article-year observations | 10,947,398 | 6,243,544 | 4,703,854 | 2,696,929 | 1,857,319 | 3,361,745 | 2,611,750 |
| Log likelihood       | -17,010,037         | -10,262,936   | -6,741,759         | -4,421,808   | -2,684,950   | -5,563,598   | -3,754,028   |

**Note.**—Estimates stem from fixed effects Poisson specifications. For each article, one observation per year is included in the sample in the window between the year of publication and 10 years after the (possibly counterfactual) event or 2006, whichever comes earlier. The dependent variable is the total number of citations accrued to a publication in a particular year. All models incorporate a full suite of year effects and nine article age effects, as well as a term common to both treated and control articles that switches from 0 to 1 after the death of the scientist, to address the concern that age, year, and individual fixed effects may not fully account for transitory citation trends after death. Exponentiating the coefficients and differencing from 1 yields numbers interpretable as elasticities. For example, the estimate in col. 1 implies that the papers of deceased scientists posthumously experience a $100 \times (\exp(0.07) - 1) = 7.25\%$ statistically significant increase in the number of citations relative to papers whose author remained alive. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to articles for which there is no variation in activity across the entire observation period. This is also true for the results reported in tables 4–6. Robust (quasi-maximum likelihood) SEs are in parentheses, clustered at the level of the star scientist.

* $P < .10$.
* $P < .05$.
** $P < .01$.
their passing, especially if the news of the eminent scientist’s illness spreads in the “invisible college” in which she or he participates.28

With regard to the second issue, we find that the citation boost that a scientist receives as a result of premature death is greater when the death occurs at a relatively young age. The overall difference can be seen most clearly from the comparison of figures 5B and 5C, given the stronger tendency toward reversion in later years among scientists who were older at the time of death. The overall difference is relatively slight, however, and is only statistically significant when the comparison is within scientists who die suddenly (whereas the difference is reversed when the comparison is within scientists whose deaths were anticipated). This could be because such deaths are experienced by the community as especially tragic (with particular sensitivity to the work the scientist might have produced had she lived), thereby triggering an especially strong mobilization on the part of the sales force.

Table 4 splits the sample over article-level characteristics that should correlate with the salience of discrete academic works within a larger portfolio of published articles for each scientist. The average effect (reproduced in col. 1) conceals striking heterogeneity in the magnitudes that apply to articles of different initial impact, assessed by cumulative citations received up to the year of death (or counterfactual death). For the articles that had already attracted the most notice at the time of death, either in a local (own top 10%) or global (universe top 1%) sense, the posthumous increase in citations is more than 17% (cols. 4 and 5), while for the least well-cited articles at the time of death (own bottom 10%), the boost is an even more remarkable 91% (col. 2). The papers that lie between the 25th and 75th percentile of citation impact at the time of death (col. 3) do not experience a posthumous citation boost. Finally, recently published articles, which are presumably salient in citers’ minds, experience a somewhat greater increase (10.1%) than articles published earlier. These analyses imply that the increased attention received by the articles of deceased scientists after their passing is not uniformly distributed across their portfolio: the broad middle of the impact distribution receives no citation boost, while articles in the tail, and particularly the bottom tail, experience an upward shift in their citation trajectory. These contributions would have remained relatively obscure had their last author not prematurely died.

Table 5 reports the results with regard to engagement style. Columns 1 and 2 report estimates for the sample split across the median of the size of the sales force distribution and show that the postdeath effect is driven by the sample of stars who cultivated a larger number of coauthors while alive.

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28 Note, however, that anticipated deaths do not exhibit elevated rates of “recognition events” in the year of a scientist’s death—or the two years that precede it—relative to scientists whose death was likely sudden.
FIG. 5.—Effect of scientists’ deaths on reception of their work—event study graphs: A, all ages, all causes of death; B, all causes of death, ≤65 at time of death; C, all causes of death, >65 at time of death; D, all ages, sudden deaths; E, all ages, anticipated deaths. Dots correspond to coefficient estimates stemming from conditional (scientist) fixed effects Poisson specifications in which citation flows are regressed onto year effects, article age effects, as well as 15 interaction terms between treatment status and the number of years before/after the death of the author (the indicator variable for treatment status interacted with the year of death is omitted). The specifications also include a full set of lead
and lag terms common to both the treated and control articles, to fully account for transitory trends around the time of the event. The 95% confidence interval (corresponding to [quasi-maximum likelihood] robust SEs, clustered at the level of the scientist) around these estimates is plotted with bars. A, B, and C correspond to dynamic versions of the specifications in table 3 columns 1, 2, and 3, respectively.

FIG. 5.—(Continued)
Columns 3 and 4 correspond to a sample split across the median of our proxy for self-promotional behavior. We find that the postdeath citation boost is twice as large in magnitude for the subsample of articles of more “humble” stars, consistent with the view that the salesman’s promotional activities are discounted by the audience. However, we caution that the standard errors around the estimates are sufficiently large that we cannot reject the hypothesis that the two coefficients are in fact equal.

The results with regard to citer identity are presented in table 6. Note that the different columns do not correspond to splits of the sample; rather, it is only the dependent variable that changes across specifications. For instance, column 1 models the effect of the scientist’s passing on the number of citations solely coming from articles that do not include a former collaborator of the deceased (or of the still-living control scientist). Overall, there is only modest evidence that postdeath citations are bestowed on the work of deceased scientists disproportionately by more proximate citers. While the magnitudes are higher for proximate citations (especially in the intellectual and spatial dimensions), the difference between the effect on proximate versus nonproximate citations is not itself statistically significant. We tentatively conclude that the citation boost documented in tables 3 and 4 (as well as fig. 5) reflects a diffuse and increased interest in the deceased’s contributions.
|                         | All Publications | Own Bottom 10% | Own 25%–75% | Own Top 10% | Universe Top 1% | 3 Years before Death |
|-------------------------|------------------|----------------|-------------|-------------|-----------------|-----------------------|
| After death             | .07*             | .65**          | .00         | .17**       | .16**           | .10*                  |
|                         | (.03)            | (.08)          | (.03)       | (.04)       | (.05)           | (.04)                 |
| No. of investigators    | 9,038            | 4,333          | 8,422       | 6,035       | 4,346           | 6,244                 |
| No. of source articles  | 481,337          | 17,747         | 264,631     | 55,558      | 25,197          | 51,930                |
| No. of source article-year observations | 10,947,398       | 368,091        | 5,945,660   | 1,351,435   | 580,912         | 610,367               |
| Log likelihood          | −17,010,037      | −483,644       | −9,030,902  | −2,427,679  | −1,182,256      | −1,132,866            |

**NOTE.**—Estimates stem from conditional fixed effects Poisson specifications. For each article, one observation per year is included in the sample in the window between the year of publication and 10 years after the (possibly counterfactual) event or 2006, whichever comes earlier. The dependent variable is the total number of citations accrued to a publication in a particular year. All models incorporate a full suite of year effects and nine article age effects, as well as a term common to both treated and control articles that switches from 0 to 1 after the death of the scientist, to address the concern that age, year, and individual fixed effects may not fully account for transitory citation trends after death. Column 4 (col. 2) corresponds to an estimation sample comprising solely the top 10% (bottom 10%) of each scientist’s publications, ranked in terms of cumulative citations at the time of death (or counterfactual time of death for control scientists). Column 3 limits the estimation sample to publications in the middle two quartiles of the citation distribution at the time of death. Column 5 limits the estimation sample to articles that fall above the 99th percentile of the vintage-specific citation distribution at the time of death in the universe of publications indexed by PubMed and the Web of Science. Exponentiating the coefficients and differencing from 1 yields numbers interpretable as elasticities. For example, the estimate in col. 1 implies that the papers of deceased scientists posthumously experience a $100 \times (\exp[0.07] - 1) = 7.25\%$ increase in the number of citations relative to papers whose author remained alive. The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to articles for which there is no variation in activity over the entire observation period. This is also true for the results reported in tables 3, 5, and 6. Robust (quasi–maximum likelihood) SEs are in parentheses, clustered at the level of the star scientist.

* $P < .10$.
* * $P < .05$.
** ** $P < .01$. 
The Determinants of Individual Academic Recognition

In clear violation of informational inefficiency, the results above demonstrate that the reception of scientists’ work does change after their death, with articles by the deceased being shifted to a steeper citation trajectory relative to the articles of the living. This posthumous boost is particularly large for articles that had not attracted wide recognition and for young scientists who die suddenly. As a whole, the evidence suggests that death elicits a surge in interest in the deceased scientist’s work relative to comparable work by still-living scientists.

### Table 5

| NO. OF COAUTHORS | Self-Promotion |
|------------------|----------------|
|                  | Below Median   | Above Median |
|                  | (1)            | (2)          | Below Median | Above Median |
| After death      | .02            | .12**        | .10**        | .05 |
|                  | (.04)          | (.04)        | (.04)        | (.05) |
| No. of investigators | 7,248         | 4,298        | 7,291        | 2,848 |
| No. of source articles | 244,293       | 237,044      | 240,139      | 241,198 |
| No. of source article-year observations | 5,544,118     | 5,403,280    | 5,171,366    | 5,776,032 |
| Log likelihood   | -8,105,971     | -8,883,461   | -8,046,445   | -8,958,661 |

**Note.**—Estimates stem from conditional fixed effects Poisson specifications. For each article, one observation per year is included in the sample in the window between the year of publication and 10 years after the (possibly counterfactual) event or 2006, whichever comes earlier. The dependent variable is the total number of citations accrued to a publication in a particular year. The estimation samples in each column correspond to sample splits across the median of two individual characteristics of the scientists in the sample, assessed in the year of death: accumulated number of distinct collaborators and self-promotion behavior. All models incorporate a full suite of year effects and nine article age effects, as well as a term common to both treated and control articles that switches from 0 to 1 after the death of the scientist, to address the concern that age, year, and individual fixed effects may not fully account for transitory citation trends after death. Exponentiating the coefficients and differencing from 1 yields numbers interpretable as elasticities. For example, the estimate in col. 2 implies that the papers of deceased scientists with above the median number of coauthors at the time of their death posthumously experience a $100 \times (\exp[0.12] - 1) = 12.75\%$ increase in the number of citations relative to papers whose author remained alive (and are also below the median number of coauthors at the time of their counterfactual death). The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to articles for which there is no variation in activity over the entire observation period. This is also true for the results reported in tables 3, 4, and 6. Robust (quasi–maximum likelihood) SEs are in parentheses, clustered at the level of the star scientist.

* $P < .10.$
* $P < .05.$
** $P < .01.$

The Determinants of Individual Academic Recognition
**TABLE 6**

**Effect of Scientist's Death on Citation Rates, by Citer Identity**

| SPACE            | Noncoauthored Cites (1) | Coauthored Cites (2) | Out-of-Field Cites (3) | In-Field Cites (4) | Noncolocated Cites (5) | Colocated Cites (6) |
|------------------|-------------------------|----------------------|------------------------|-------------------|------------------------|---------------------|
| SOCIAL SPACE     | 0.06                   | 0.07                 | 0.07                   | 0.17              | 0.06                   | 0.18                |
| INTELLECTUAL     |                         |                      |                        |                   |                        |                     |
| SPACE            |                         |                      |                        |                   |                        |                     |
| GEOGRAPHIC SPACE |                         |                      |                        |                   |                        |                     |

Note: Estimates stem from fixed effects Poisson specifications. For each article, one observation per year is included in the sample in the window between the year of publication and 10 years after the (possibly counterfactual) event or 2006, whichever comes earlier. The dependent variable is the total number of citations from colocated authors vs. distant authors. All models incorporate a full suite of year effects and nine article age effects, as well as a term common to both treated and control articles that switches from 0 to 1 after the death of the scientist to address the concern that age, year, and individual fixed effects may not fully account for transitory citation trends after death. Exponentiating the coefficients and differencing from 1 yields numbers interpretable as elasticities. For example, the estimate in col. 6 implies that the papers of deceased scientists experience a posthumous 19.72% increase in the number of citations from colocated scientists. All use subject to University of Chicago Press Terms and Conditions (http://www.journals.uchicago.edu/t-and-c).
What these results do not explain, however, is why this mobilization occurred. In the second and third steps of our analysis, we examine the possibility that supporters of the deceased scientist promote her work via recognition events, whereas such interested promotion does not occur, or occurs with less intensity, for still-living scientists.

To measure the determinants of academic recognition at the scientist level, we model the probability of being memorialized (for the deceased) or recognized (for the still-living controls) at least once in an academic journal within a window of one year before to four years after the year of death (or counterfactual death). In the sample of 9,046 scientists, our minimal list of covariates to explain recognition includes an indicator variable for the deceased, the scientist’s gender, her age in the year of death (captured with six indicator variables corresponding to different brackets, e.g., less than 45 years old, between 45 and 55 years old, etc.), indicator variables for the cause of death (anticipated death is the omitted category), and a full suite of indicator variables for the calendar year of death.29

Table 7 reports marginal effects from logit models. Consistent with figure 4, the estimates in column 1 demonstrate that the deceased are more than 18% more likely to be recognized (at the means of the other covariates). Conversely, there does not seem to be much difference between the likelihood of recognition for scientists of different genders (with the caveat that the gender composition of the sample skews heavily male). We do not report the coefficients for the included age effects, but the age gradient is relatively flat, except at very old ages—the “forces of nature” who die past age 75 while still leading an active scientific career get memorialized more intensely than scientists whose death can more legitimately be deemed “premature.”

Columns 2–4 of table 7 examine the role of eminence in shaping the intensity of recognition. All columns include an indicator variable for members of the NAS, which can be thought of as an “elite within the elite.” The effect of NAS membership is always large and precisely estimated. Column 2 uses cumulative citations at death as an additional measure of eminence. Column 3 (respectively, col. 4) uses cumulative publications instead (respectively, cumulative NIH funding). The results indicate that eminence is, perhaps unsurprisingly, correlated positively with recognition. Column 5 includes all three measures in the specification, but the high correlation between them makes it difficult to interpret the results (although the cumulative citation measure is the one that appears to keep its sign and magnitude).

Columns 6 and 7 of table 7 retain eminence as a covariate (using NAS membership and citations at death) but also add two measures that aim to capture the size of the cohort of scientists who are probably most affected

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29 Recall that still-living scientists inherit both the year of death and the cause of death of the deceased scientist with whom they are matched in our research design.
by the premature death of a scientist: former trainees and collaborators of the deceased, respectively.\textsuperscript{30} The results in columns 6 and 7 do not seem

\textsuperscript{30} Trainees are identified as the subset of coauthors who appear in first-authorship position when the star is in last-authorship position, in a window of five years around the time they earned their highest degree.
to indicate that the sheer quantity of trainees and former collaborators (which we might think of as constituting the deceased’s “visible college”) correlates strongly with memorialization activities. Column 8 presents the results for the most saturated model, which adds our index of self-promotional behavior as a covariate. We find that self-promotion is positively correlated with recognition. At the very least, it does not appear that humility makes it easier for the sales force to coalesce around the memory of the deceased.

Since the postdeath citation boost was especially startling for younger scientists, we also explore whether the age-recognition gradient differs for deceased and still-living scientists. We do so by including age at death × treatment status interactions in the memorialization regression model and displaying the marginal effects in figure 4B. Older scientists may be more memorialized than younger ones on average, but at every age, and especially younger ones, scientists who die get memorialized more than those who remain alive. Thus, consistent with Lang and Lang (1988), and consistent with the findings of the difference-in-differences model, the type of recognition events that accrue to very senior scientists in the twilight of their careers (or in retirement) are bestowed onto younger scientists only if they die prematurely.

Table E3 in the online appendix examines the authors of academic memory events in the subsample of 720 deceased scientists and demonstrates that the memorializers are either socially connected (coauthor or former trainee), intellectually connected (same subfield), or spatially connected (same institution) with the individual they recognize. The evidence is therefore consistent with a particular sequence unfolding after the death event, whereby close associates take on the burden of memorializing the deceased, and in certain conditions this triggers a much wider and diffuse response that expresses itself in the form of an elevated propensity to cite the work of the deceased. The next section attempts to substantiate empirically the last step of this sequence.

Long-Run Citation Afterlife and Its Relationship to Recognition Efforts

For the final step of our analysis, we test whether recognition events in a limited window around the time of death (or counterfactual death) mediate the effect of a scientist’s passing on the rate of long-run posthumous citations for articles that were published before the death occurred. To do so, we regress “excess” cumulative citations on an indicator variable for the deceased, the intensity of recognition activity, along with the following covariates as controls: year of publication effects, gender, degree type, an indicator variable for sudden deaths and unknown causes of death, as well as a full set of indicator variables for the scientist’s age at the time of death and for his or her calendar year of death. Because recognition efforts might have a nonlinear relationship with long-run citations, we break out the overall count of
academic recognition events: zero events (89.2% of the articles, the omitted category), exactly one recognition event (6.9% of the articles), exactly two recognition events (2.1% of the articles), and three or more recognition events (1.8% of the articles).

Table 8 reports OLS estimates. Because the distribution of excess citations is skewed and takes on negative values, we model it using a NegLog transformation (Yeo and Johnson 2000). In columns 1–3, we use all possible citations to build a predicted count for the “surprise” in citations for each article published by a scientist in the postdeath period. In columns 4–6, we use the same predictive model but omit citations that accrue in the five years that immediately follow the death (as well as citations from articles

### TABLE 8
LONG-RUN CITATION AFTERLIFE AND ITS RELATIONSHIP TO RECOGNITION EFFORTS

|                      | ALL CITATIONS | EXCLUDING CITATIONS IN A WINDOW OF 5 YEARS |
|----------------------|---------------|--------------------------------------------|
|                      | (1) | (2) | (3) | (4) | (5) | (6) |
| Deceased             | .11** | .06 | .10** | .08* |     |     |
|                      | (.04) | (.04) | (.03) | (.03) |     |     |
| Scientists with 1 academic memory/recognition | .18** | .17** | .11** | .10** |     |     |
|                      | (.04) | (.04) | (.03) | (.03) |     |     |
| Scientists with 2 academic memories/recognition | .21** | .20** | .13** | .12** |     |     |
|                      | (.05) | (.05) | (.04) | (.04) |     |     |
| Scientists with 3+ academic memories/recognition | .21** | .20** | .12** | .11* |     |     |
|                      | (.05) | (.06) | (.05) | (.05) |     |     |
| Mean of dependent variable | -.88 | -.88 | -.88 | -.44 | -.44 | -.44 |
| Adjusted R²          | .05  | .05  | .05  | .16  | .16  | .16  |

**NOTE.**—Estimates stem from ordinary least squares specifications. The dependent variable is the number of “excess” citations, which is simply the number of actual posthumous citations minus the number of predicted posthumous citations, based on the prediction model presented in online app. D. In cols. 1–3, all postdeath/post–counterfactual death citations are used to compute the prediction, whereas in cols. 4–6, citations that accrue in the first five years after death are excluded, as well as citations given by collaborators and memorializers of the deceased. Because the distribution of excess citations is both skewed and takes on negative values, a NegLog transformation of the dependent variable (Yeo and Johnson 2000) is performed before estimation. All models include (but do not report coefficients for) a full suite of indicator variables for age at death, year of death, year of the article’s publication, degree type, and cause of death. Number of source articles = 481,746; number of investigators = 9,046. Robust SEs, clustered at the level of the scientist, are in parentheses.

* P < .10.
* * P < .05.
* ** P < .01.
written by coauthors or memorializers) to compute the prediction. The reason to exclude citations that accrue to the scientists’ articles in the immediate aftermath of their deaths (or counterfactual deaths) is that these citations could reflect, at least in part, recognition efforts (e.g., it is not uncommon for obituaries and reminiscences published in scientific journals to have a list of references). By excluding from the count of excess citations those that accrue in the period of bereavement (or counterfactual bereavement), we can be more confident that our measure of excess citations does not reflect the mechanical impact of memorialization efforts.

In table 8, column 1, we confirm the effect found in the difference-in-differences analysis: the articles of deceased scientists receive 11.2% more posthumous citations on average, relative to those of still-living scientists. Results in column 2 are consistent with our argument that assigns a key role to recognition events: recognized scientists exhibit elevated rates of posthumous citations, relative to unrecognized ones. Column 3 simultaneously enters the deceased effect and the effects for the recognition events in the model. The magnitude of the deceased effect is halved and becomes imprecisely estimated. In contrast, the magnitudes of the recognition effects remain largely unchanged. From this analysis, it would appear that recognition processes largely mediate the effect of death on the allocation of the scientific community’s attention toward scientific works that appeared before the death.31

The models in table 8, columns 4–6, paint a similar qualitative picture, with the caveat that the attenuation of the coefficient estimate for the effect of death itself is less stark in these models, which omit the short-run citation response.32 In spite of this, the correlation between recognition intensity and posthumous citations does not appear to merely reflect awareness by the “visible college” during the turbulent years that immediately follow the passing of these scientists.

A necessary caveat is that the validity of a mediation analysis of this type requires (i) the absence of unmeasured treatment-outcome confounders, conditional on control covariates, and (ii) the absence of unmeasured mediator-outcome confounders, also conditional on covariates (Shaver 2005). The first assumption might be valid in our application, if we assume death to be an exogenous event.33 The second assumption strikes us as being less tenable,

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31 Using a more parsimonious model with a single dichotomous mediator (recognized at least once vs. not), we perform a Sobel (1982) test and find that 41.1% of the effect of death is mediated by the recognition effect.

32 The Sobel test implies that only 37.3% of the treatment effect of death is mediated by the recognition effect in this case.

33 But even the exogenous character of death is open to challenge in our setting: in the case of anticipated events, elite scientists might have the opportunity to actively shape their legacy, including the identity of their future memorializers.
since more recognized scientists might differ from less recognized ones in myriad other ways that also correlate with unobserved determinants of posthumous citation rates. In the absence of exogenous variation in memorialization intensity, the evidence of partial mediation presented in table 8 must be considered as merely suggestive: individual recognition plausibly contributes to the triggering of a vibrant “citation afterlife” for deceased scientists.

When considered in the context of the results presented in tables 3–7, the evidence points to the following chain of events: the death of eminent scientists activates a narrow vanguard of colleagues who were proximate to the deceased.\textsuperscript{34} It is this vanguard who engages in memorialization efforts, and these efforts in turn bring to the attention of the scientific community at large the work of the deceased—in particular, work that may have been overlooked while he was alive.

CONCLUSION AND DISCUSSION

Limitations

Before concluding, it is useful to consider our findings in light of the two principal limitations of our study: that our sample is limited to elite academic life scientists and that our method for identifying the effect of interested promotion focuses on the shock of a scientist’s premature death. Recall that the main advantage of our sample is that the wealth of information on elite life scientists allows us to create precise and meaningful counterfactuals. And the main advantage of focusing on the effects of death is that the death of a scientist occasions a shift in promotional activity without any change in the underlying quality of what was produced. But to what extent do our findings generalize beyond what we can observe with this sample and method?

Regarding the limitations of focusing on elite scientists, some light may be shed by examining the variation in status within our sample. To see if higher status scientists receive a larger boost in citations after their death, we reprise the difference-in-differences empirical framework and split the sample at the median by cumulative publications, citations, and funding at the time of death. No clear pattern emerges from these analyses—displayed in table 9—except that the effect of death remains positive across all sample splits. The articles of more eminent scientists may experience a larger boost than those of the less eminent (when eminence is measured by cumulative publications at death) or a smaller boost (when eminence is measure by cumulative citations or funding at death). Moreover, in all cases the

\textsuperscript{34} Proximity is multidimensional, corresponding to relationships that unfolded in geographic space (such as the case of department or university colleagues), in social space (such as between mentor and trainee or between coauthors), and in intellectual space (such as shared topics, research questions, and methodologies).
| Heterogeneity in the Effect of Scientist’s Death on Citation Rates, by Scientist Status |
|----------------------------------------------------------|
| **Publications** | **Citations** | **Funding** |
| Below Median | Above Median | Below Median | Above Median | Below Median | Above Median |
| (1) | (2) | (3) | (4) | (5) | (6) |
| After death | .04 | .11* | .09** | .06 | .09* | .05 |
| (0.03) | (0.05) | (0.03) | (0.05) | (0.05) | (0.05) |
| No. of investigators | 8,253 | 2,859 | 7,759 | 3,052 | 7,703 | 3,277 |
| No. of source articles | 241,403 | 239,934 | 239,165 | 242,172 | 240,863 | 221,903 |
| No. of source article-year observations | 5,253,983 | 5,693,415 | 5,393,368 | 5,554,030 | 5,176,767 | 5,358,076 |
| Log likelihood | -7,982,519 | -9,020,775 | -7,062,688 | -9,934,474 | -7,966,382 | -8,359,278 |

Note.—Estimates stem from conditional fixed effects Poisson specifications. For each article, one observation per year is included in the sample in the window between the year of publication and 10 years after the (possibly counterfactual) event or 2006, whichever comes earlier. The dependent variable is the total number of citations accrued to a publication in a particular year. The estimation samples in each column correspond to sample splits across the median of three individual scientist characteristics assessed in the year of death: cumulative publications, cumulative citations, and cumulative National Institutes of Health (NIH) funding. All models incorporate a full suite of year effects and nine article age effects, as well as a term common to both treated and control articles that switches from 0 to 1 after the death of the scientist, to address the concern that age, year, and individual fixed effects may not fully account for transitory citation trends after death. Exponentiating the coefficients and differencing from 1 yields numbers interpretable as elasticities. For example, the estimate in col. 2 implies that the papers of deceased scientists with above the median number of publications at the time of their death posthumously experience a $100 \times (\exp(0.11) - 1) = 11.63\%$ increase in the number of citations relative to papers whose author remained alive (and are also below the median number of publications at the time of their counterfactual death). The number of observations varies slightly across columns because the conditional fixed effects specification drops observations corresponding to articles for which there is no variation in activity over the entire observation period. Columns 5 and 6 drop from the sample articles written by 318 scientists (273 treated scientists and 45 control scientists) who are “intramural employees” of the NIH and therefore not eligible to receive extramural NIH funds. Robust (quasi–maximum likelihood) SEs are in parentheses, clustered at the level of the star scientist.

* $P < .10$.
* * $P < .05$.
** $P < .01$. 
difference between the above-median and below-median coefficients is not itself statistically significant. Therefore, the data at our disposal do not support the idea that the efficacy of interested promotion varies with a scientist’s status.

Yet there remain reasons to doubt that we can generalize from an elite sample to the general population of scientists. It is possible that interested promotion is more efficacious for lower-status scientists. This possibility is foreshadowed by the literature on the Matthew effect in that it highlights how the work of high-status scientists is more widely read (Merton 1968; Cole 1970; Allison, Long, and Krauze 1982; Simcoe and Waguespack 2011; Azoulay et al. 2014). Insofar as this is the case, it may be that the work of elite scientists is relatively insensitive to promotional efforts in general and posthumous memorialization in particular. Put differently, while we find that even the highest-status scientists have some work that has been overlooked by the community and is thus sensitive to interested promotion, this should a fortiori be true for low-status scientists. But while the efficacy of equivalent promotional activity may be greater for lower-status scientists, it may be more difficult to mobilize (posthumous) activity for such scientists. Our results regarding the correlates of individual academic recognition (e.g., table 7) demonstrate significant responsiveness to status differences. Since such efforts partly mediate the effect of death on posthumous citations (table 8), it follows that one might expect the death of lower-status scientists to be less effective in mobilizing a sales force and for this smaller sales force to be less effective in activating the community at large to pay homage to the work of the deceased. Finally, it is also possible that interested promotion would be less valuable for lower-status scientists because audiences will find efforts to promote their work less credible.

Putting aside how the rate and effect of interested promotion might vary with the status of the scientist, promotional activities may vary with other contextual factors that are held constant in our study. In particular, it may be that the death of a scientist is an unusually good context for promoting her work because the norm of disinterestedness is suspended. The occasion of a death may also lend unusual credibility to assessments of a scientist’s work because they occur sometime after publication and thus are not a snap judgment but can be made in light of subsequent work. Finally, since we identified the salesman effect indirectly, via the absence of a drop in citations due to death, there is reason to wonder whether scientists can sometimes be more effective as salesmen than our study suggests.

The literature on the Matthew effect would also suggest that lower-status scientists attract smaller numbers of coauthors, research assistants, doctoral students, and admirers (see Zuckerman 1967; Allison and Stewart 1974; Goldstone 1979; Stewart 1983; Rossiter 1993; Dey, Milem, and Berger 1997)—in other words, a less vibrant sales force.
The upshot is that the current study is hardly the last word on how interested promotion skews scientific valuation or social valuation more generally. Our results provide evidence for informational inefficiency in a highly developed and broad scientific domain, but they are particular to that domain and a particular select group within it, a particular social cue, and a particular opportunity for viewing the effects of that social cue. Our discussion here provides some guidance for how our results may generalize along those dimensions, but we must await future research before drawing firmer conclusions.

Implications

The foregoing caveats notwithstanding, our study has significant implications for understanding the informational (in)efficiency of meritocratic systems, how science as a vocation shapes recognition and the allocation of credit, and reputational entrepreneurship more generally. We conclude by discussing each of these implications in turn.

The informational efficiency of meritocratic systems.—An important contribution of our article is to open up a new direction for the study of how social cues affect the informational efficiency of meritocratic systems. As reviewed above, recent research has made significant strides on this question. However, this literature is also limited because of the narrow range of social cues and situations it has examined. In short, it is potentially quite problematic to reduce all social cues to disinterested validation. One important limitation of this restricted focus has been stressed by some scholars (see Zuckerman 2012a, pp. 227–30; Turco and Zuckerman 2017, p. 1287) but not fully appreciated in the literature, that is, that anonymous evaluators (as in Salganik et al. [2006] or van de Rijt [2019]) are unusually impervious to social influence. In many social settings, actors are highly sensitive to the popularity of a practice or product, sometimes conforming and sometimes differentiating from others based purely on the prevalence and identity of others who have adopted it (e.g., Lieberson and Lynn 2003; Obukhova, Zuckerman, and Zhang 2014; Catalini and Tucker 2017). As such, whereas some scholars have concluded from studies of anonymous evaluators that social cues have limited impact in skewing valuations in meritocratic settings (see Salganik and Watts 2008; van de Rijt 2019), this conclusion is premature.

To be sure, some studies have indeed examined disinterested validation in settings where valuations are not anonymous. For example, studies based on natural experiments in scientific domains are focused on environments where the evaluators may be quite sensitive to the impressions their
evaluations make on others. In particular, scientists may often be reluctant to cite work that is rarely cited by others (or perhaps by lower-status scientists). Given that, it is notable progress to find that disinterested validation is responsible for a significant if modest degree of informational inefficiency (Simcoe and Waguespack 2011; Azoulay et al. 2014). Yet without broadening the social cues examined, from disinterested validation to interested promotion, our knowledge of how social cues affect informational efficiency is quite limited. It is unclear why (with the exception of the literature on reputational entrepreneurship) scholars have focused on disinterested validation rather than interested promotion. One possibility is that it is challenging to study promotional activity in the laboratory, at least in a manner that would be generalizable. A second possibility is that scholars tend to assume that scientific fields, and meritocratic systems more generally, are governed by the Mertonian norms of disinterestedness and universalism. We have given ample reason not to rely on such an assumption, however. In light of the information frictions documented here and prior research, scientific communities may find it difficult and undesirable to dismiss promotional efforts, as they may have useful information in them. This ambiguity may make interested promotion an effective means of boosting valuations, both by the focal scientist and by her supporters.

If either the avowed norms of science were fully operative or the mechanisms underlying the scientific marketplace worked to distinguish better from worse work (given established paradigms), it would not matter whether the author of a scientific paper is dead or alive. But we find that it does matter, thus indicating the weakness of such norms and the limits to informational efficiency. In particular, the random event of an untimely death elicits commemoration activity, and such activity seems to raise the valuation of elite scientists’ lesser-known work. As noted, these findings are hardly definitive. But insofar as we have identified a class of important social cues that shape valuations in meritocratic systems, future work will help flesh out our understanding of such effects given a wider range of social cues and social contexts.

36 Note, however, that when evaluators are highly sensitive to making unusual valuations, this provides another reason why a system can be allocationally inefficient even while achieving informational efficiency. At the limit, if everyone conforms to established views, reactions to new work will be consistent but progress will never be recognized.

37 As Arnout van de Rijt helpfully pointed out to us, an additional dimension along which social cues vary is the extent to which they occur via relationships. Thus, the mode of social influence found in book clubs (Rawlings and Childress 2019) is distinct from either that which occurs via the canonical studies of disinterested validation or the kind of interested promotion we have studied in this article—both of which operate largely outside direct relationships. A full account of how social cues skew valuations should consider this additional dimension.
How science as a vocation shapes recognition and the allocation of credit.— A second contribution of our article is to shed light on how careers within science shape the allocation of credit. Misvaluations arise in part because science struggles to divorce research from the identity of its author. The norms of disinterestedness and universalism belie the fact that science is a profession through which many individuals seek employment, status, and remuneration (Polanyi 1966; Merton 1968; Gieryn 1983). While scientific communities may seek to evaluate contributions in a manner that is blind to the identity of contributors, members can hardly be blind to identity when they recruit individuals to teach and to manage laboratories. Similarly, while citations and various awards may be conferred on papers, grants and other awards are given to individuals for broad research agendas. The paradox is that the scientific community is committed to assessing work independently of its producers even while evaluating producers on the basis of their work. This tension between universalism and science as an employment system is most observable in the debate over the “blinding” of the review process; although double-blinded reviews are most common in science, there is significant controversy over the practice precisely because some explicitly wish to use the author’s identity as a signal of quality (Ceci and Peters 1984; Blank 1991). While the salience of identity to the valuation of scientific work is not new in the context of this debate, we demonstrate that even outside of it (or more specifically after it), the identity of the author materially affects the valuation of scientific work.

This struggle shows science to be nearer to art in its evaluation of work than it would at first appear to be. There is little debate that the value of a work of art is greatly affected by the identity of the artist. The salience of the artist’s identity arises from the fact that art is assessed through the lens of the artist’s style (Sgourev and Althuizen 2014; Wohl 2019). For this reason, art exhibitions are typically organized by artist (within genre) and reviews are most often done by well-known critics when the identity of both parties is plainly visible. Science at first blush seems to be organized in stark contrast, all in accordance to the norm of universalism (Merton 1979). But our findings demonstrate that these institutional arrangements are insufficient to overcome the incentives created by the employment and status system of science. Just as in the case of Lang and Lang’s (1988) etchers, the valuation of scientific works is affected by the identity of the author via efforts at interested promotion. Discussions of a scientist’s oeuvre at a retirement Festschrift or a memorial event bear many of the hallmarks of parallel events in the art world.

The logic of interested promotion.—Finally, our analysis advances our understanding of how interested promotion shapes producer legacies. Past
research in this area (labeled “reputational entrepreneurship”) has focused on politics and art (Lang and Lang 1988; Fine 1996; Bromberg and Fine 2002; Jansen 2007; Kahl, Kim, and Philips 2010; McCormick 2015). This study used the context of science to analyze how a scientist’s death affects the amount of interested promotion that her work receives, thus boosting positive recognition for her papers. This represents an advance both because this is a setting with especially strong meritocratic norms and because it allows for more careful identification. A key challenge in verifying any causal claim is to measure the impact relative to a counterfactual situation in which the event had not occurred (Lewis 1973). In politics, this is daunting because the number of observations is quite small and events are historically and contextually dependent. And identifying counterfactuals in art is challenging because of the absence of consensual criteria for judging pieces of art to be equivalent. In science, however, over 2.5 million articles are published annually after having completed peer review based on relatively consensual evaluation guidelines. As a result, we have been able to synthesize counterfactual cases in which death or interested promotion did not occur, by comparing articles with similar characteristics.

This approach yields striking results: interested promotion can permanently shift the valuation of prior work by up to 7.3% on average and upward of 90% in some cases. This research design also allows us to shed light on which actors are the most effective in promoting legacy. Prior work tended to focus on either the sales force (Lang and Lang 1988) or the salesman (e.g., Fine 1996) but tended not to directly compare the two. Our research design allows for this through the juxtaposition of living scientists and the memorializers of deceased ones. This comparison reveals the memorializers (sales force) to be more effective in changing valuations than is the scientist herself. This may reflect a very general pattern. It is intriguing to note how major religious movements (e.g., Christianity, Mormonism, Hasidism, Islam, and Buddhism) seem to get a boost from the founder’s death, as it mobilizes efforts by disciples to ensure that the founder’s life and vision are remembered and institutionalized. But why might the sales force be more effective than the salesman? Two likely (but as yet untested) reasons are size and credibility. Individuals promoting their own work may be limited in that they can only be in one place at a time; by contrast, the sales force can have a much larger presence. Additionally, while communities may discount the efforts of the salesman as being self-interested, the motives of the sales force may be more difficult to impugn. As such, the larger community may be more receptive to their message and, therefore, likely to pay more attention.

38 We are grateful to Angela Lu for pointing this out to us.
The impact of superstar scientist deaths.—Our article also sheds some initial light on how interested promotion works. Prior research on reputational entrepreneurship does not distinguish between shifts in attention and in valuation. By contrast, our results—in particular, that it is the least-cited papers that are most sensitive to reputational entrepreneurship—suggest that attentional processes may be especially important. Our study is not definitive in this regard, nor is it clear to what extent our results would generalize to domains beyond science, but they call into question a tendency to assume that reputational entrepreneurship operates by changing the valuations of existing audiences. In bringing overlooked work to the fore, the sales force is able to increase its valuation by changing the sample of work with which the community engages (Denrell and Le Mens 2016). That this mechanism is so effective in science, and especially in the work of elite scientists, is testimony to the extent to which search costs inhibit the scientific community’s ability to digest new work.

We close by reflecting on how our findings at once resonate and are in tension with broader observations concerning the role of a prominent scientist’s death in shaping her legacy. On the one hand, we have seen evidence of a general pattern by which death mobilizes (a large, credible, cadre) of supporters to promote the scientist’s legacy. On the other hand, recent research (Azoulay et al. 2019) provides systematic evidence for Max Planck’s quip that “science advances one funeral at a time.” The idea is that prominent scientists are often conservative forces because of their control of resources and opportunities, such that their removal from the scene gives innovative outsiders (identified as scientists who did not collaborate with the dead scientist) the space they need to flourish. But then is a scientist’s death a positive or a negative force from the standpoint of preserving a scientist’s legacy?

A tentative answer is that there are two countervailing effects. On the one hand, the death of a scientist gives her supporters a temporary platform for calling attention to her work, thus helping her work gain recognition relative to other work. But on the other hand, unless these supporters have effective control of their field, their temporary platform does not block the arrival of outsiders who might wish to challenge the existing paradigm with new contributions—work that soon becomes more impactful as it facilitates a paradigm shift. A possible paradox then is that while the death of elite scientists provides a glimpse into the informational inefficiency of science, it also increases the allocational efficiency of science in the long run.

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