Deadlines, Work Flows, Task Sorting, and Work Quality

Natarajan Balasubramanian, Jeongsik (Jay) Lee, and Jagadeesh Sivadasan

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Abstract

Deadlines are often used to manage the time of valuable human capital. In this multi-method paper, we propose a theoretical framework grounded in a formal model that encapsulates the key drivers and consequences of deadline-related time pressures on work flows, task sorting and work quality. We use large-scale data on patent filings along with insights from primary data collection to test our hypotheses. In line with our predictions, we find clustering of patent filings around month-ends, with month-end applications being more complex than those filed on other days. Consistent with time pressure reducing work quality, we find that work quality is lower for tasks completed at month-ends, more so for process measures of quality than for outcome measures. Calibrating our model to the data allows us to shed light on the benefits of deadlines, and suggests small levels of task acceleration but potentially larger working capital–related benefits for law firms.
1 Introduction

A critical resource-allocation challenge for managers, particularly in knowledge-intensive, high-wage sectors, is optimally managing the time of valuable human capital. In organizational settings, there are potential trade-offs between speed and performance. While increasing speed or limiting time allocated to specific tasks may increase the quantity of output and help better coordinate across tasks, the costs of doing so could include potentially poorer quality or innovativeness of work due to increased time pressure (e.g., Amabile et al., 2002; Kelly and Karau, 1999).

Firms often manage these trade-offs by using “deadlines,” or specific end-dates to complete tasks, with penalties for delaying work beyond those deadlines (Bluedorn and Denhardt, 1988; Locke and Latham, 1984; Schriber, 1986).\(^1\) Notwithstanding their ubiquity in the corporate world, large-sample studies of the effects of deadlines in real-world settings have been limited.

In this paper, we propose a theoretical framework (grounded in a formal model) that encapsulates the key drivers and consequences of deadline penalties. In our framework, set in a principal-agent context, it is optimal for the principal to impose a deadline penalty if the trade-offs seen by the agent when determining the optimal task duration are not congruent with the trade-offs perceived by the principal. Our model generates predictions for three important outcomes: (i) work flows, (ii) task complexity, and (iii) work quality. Specifically, we predict that in the presence of a deadline penalty, (i) tasks will be clustered at the period-end deadlines, (ii) tasks completed at the deadline will, on average, be of higher complexity, and (iii) work quality will be lower for tasks completed at the deadline, both unconditionally and conditional on task complexity. Our model also implies that (iv) the adoption and/or severity of deadline penalties will increase with firm size and the pace of innovation.

We then test and confirm these predictions using large-scale, high-frequency data on granted patents (about 3 million) and published patent applications (about 1.9 million) in the United States, supplemented with primary data collection efforts through interviews and surveys of inventors and patent attorneys. The unique nature of the data allows us to examine work flows, task complexity, and work quality at a level of detail that has not been possible in prior studies of deadlines and time pressure. Indeed, our setting meets the challenging data requirements for empirical analysis of the effect of deadlines in real-world settings: data on a comparable activity, and reasonably uniform measures of task complexity, and work quality across numerous firms and time periods. Because the data cover millions of patents and patent applications, we observe work flows for millions of fairly comparable tasks spread over several decades and across thousands of different firms. Our data also allow us to form a number of alternative measures for task complexity so that we can study how deadlines affect some of the tasks to be prioritized over others before the deadlines. Perhaps most importantly, the data allow us to construct numerous measures of different aspects of work quality, permitting a detailed and nuanced examination of the effects of time pressure close to deadlines.

\(^1\)Bluedorn and Denhardt (1988), in their review of the literature on time and organizations, cite Schriber (1986, p. 47) as positing that the central tasks for managers are to “set deadlines within the work unit (cycle speed and frequency, for example), negotiate interdependent deadlines with other work units (cycle interconnectedness), set and modify schedules (cycle speed, frequency and interconnectedness), configure task sets into jobs, and allocate temporal resources to them (cycle variety)”(italics added). In their early work on goal setting, Locke and Latham (1984) note that setting explicit deadlines is a normative part of setting goals effectively, and the inclusion of a deadline increases the motivational effect of a goal.
Consistent with our prediction, patent filing work flows exhibit significant clustering of filings at month-ends (Figure 2). For instance, the last working day of a month accounts for 7.0% of all patent applications filed in that month, compared with an expected uniform rate of 4.8% in the sample, suggesting that nearly a third of the applications on the last working day are related to month-end clustering. Additional clustering is also observed at typical financial quarter-ends—March, June, September, and December. These four months account for 36.3% of all successful patent filings, compared with 33% in the case of uniform filing. Several empirical tests, analyses of matched primary-secondary data, and interviews with practitioners confirm the observed clustering to be due to deadlines.

Next, we use characteristics of applications to examine task sorting around deadlines. Specifically, we use six measures that are likely to be related to the complexity of the underlying idea: the log number of claims in the application, log number of drawings, log number of drawing sheets, log number of drawings per drawing sheet, log number of forward citations, and the probability of renewal of the patent.\(^2\) Consistent with our prediction, we find robust evidence that month-end applications are of higher complexity (Figure 3). For instance, our regression estimates are equivalent to a 4.5–6.2% difference between the number of claims in applications influenced by month-end deadlines and other applications. The corresponding differences for citations and probability of renewal are 3.8–5.6% and 1.0–2.1%, respectively.\(^3\)

The final but a central piece of our empirical analysis focuses on the implications of deadlines on work quality. Based on the suggestions received during our interviews with attorneys, we look at a total of 11 measures of work quality. Eight of these measures are transactions during the prosecution (examination) of the patent by the United States Patent and Trademark Office (USPTO) and relate to work-process quality—that is, they reflect or arise from errors or omissions in the application document (for instance, “Separate Inventor Oaths” indicates that the inventor oaths were not included in the initial filing; “Restriction Requirement” means that the application contained two distinct inventions rather than one). The other three measures — share of cites that are added by the examiner, probability of application approval, and log of review duration — are work-outcome measures; unlike the process measures, these are based on outcomes observable in the patent/application data.\(^4\)

We find that all work-process quality measures are considerably lower for applications filed at month-ends, with the strongest effects generally for applications filed on the last day of the month. Among the largest magnitude of effects are the propensities for Separate Inventor Oaths (18.6% higher for last day of the month), Application Incomplete notice (15.8%), and Additional Application Filing Fees (14.8%).

The work-outcome measures also indicate poorer quality for patent filings closer to month-ends, but the magnitude of the effects is more modest. Applications filed at month-ends have more examiner-added cites (by 0.69% for the last five days of the month), a lower approval rate (by 0.55% for the last five days, which translates to a 2.26% higher probability of rejection), and a longer review duration (by 1–2.3% over the last five days of the month). The more modest effects for the work-outcome measures suggest that the short-
run corrections captured by the work-process measures moderate the long-run quality consequences of the acceleration of filings close to deadlines.

Having examined work flows, task complexity, and work-quality results for the sample as a whole, we next check if our key results vary with technology and firm characteristics as hypothesized. Because principals are likely perceive greater benefits from an earlier priority date, we may expect more widespread use of deadlines (and/or stronger deadline penalties) in technologies with a rapid pace of innovation. Indeed, we find that month-end clustering behavior is more pronounced in such technologies. Importantly, our results on complexity and work quality are also stronger in such technologies, consistent with our inference that these effects are driven by deadline penalties. Because monitoring and enforcing deadline penalties are likely to involve fixed costs, we expect firms with larger patent volume to be more likely to adopt deadlines. We find this to be true. As expected, we find stronger complexity and work-quality results for larger firms. These two sets of results significantly strengthen our interpretation of the baseline results for month-end clustering, complexity and work quality as being driven by month-end deadlines.

Finally, we undertake a calibration exercise that allows us to evaluate potential benefits of deadlines and perform interesting counterfactual analyses. Our analysis shows that for our baseline scenario (with penalties for billing deadlines every 22 days calibrated to match the observed amount of month-end clustering in the data), time savings from acceleration of jobs are quite modest (1.8%) relative to the increase in error rate (12%), but this small acceleration leads to a significant saving in terms of working capital requirements (31.6% saving in days of unbilled balances) for the accelerated tasks.

On the whole, our study makes several important contributions to a number of related fields of research, with implications for management. First, our analysis of work flows contributes to the literature in labor and personnel economics that has examined how incentives affect work outcomes including timing of effort. Although we are the first (to our knowledge) to examine the effects of deadlines on patent application work flows, our results are consistent with findings in this literature that document agents’ modification of the timing of work efforts in response to incentives (e.g., Asch, 1990; Courty and Marschke, 1997; Oyer, 1998).5

Second, the potential effect of deadlines on task sorting has, to our knowledge, not previously been investigated in the literature. Our finding of higher complexity of tasks completed close to deadlines provides a novel stylized fact, consistent with the model we propose. As we show in our model, this result is non-trivial; the prediction of higher complexity at the deadline hinges on the error rate not increasing too fast with complexity relative to how fast the deadline penalty changes with complexity.6 In most modern organizations, workers and work groups simultaneously undertake multiple tasks of varying complexity, and managers are required to synchronize or coordinate across different tasks and work groups. Our finding provides suggestive evidence that stronger penalties are imposed on more-complex tasks, which is consistent with a number of the motivations we discuss for the imposition of the deadline penalty.7

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5 For example, in an interesting study, Oyer (1998) exploits variations in fiscal year-ends to document that manufacturing firm sales are higher at the end of the fiscal year and lower at the beginning, suggesting that salespersons and executives respond to convex incentives that induce them to cluster effort in the last quarter of the firm’s fiscal year.

6 In particular, if the error rate increased fast enough and more-complex tasks were penalized less, in equilibrium the complexity of tasks completed at the deadline could be lower than at other times.

7 In particular, concerns for the principal relating to coordination, expenditure accounting, working capital needs, and the agent’s
Third and perhaps most importantly, our findings directly speak to the literature on how time pressure affects work quality. While not focused on the effect of deadlines per se, parts of the rich literature in psychology, organizational behavior, and management on the effects of time pressure address the question of if and how time pressure affects work quality. The empirical work in this literature has yielded mixed results. Although some of the earlier work (e.g., Kelly and McGrath, 1985) found a negative effect of time pressure on performance quality, Isenberg (1981) and Karau and Kelly (1992) found evidence for a non-linear relationship, with the best outcomes achieved under moderate levels of time pressure. In contrast, a positive relationship between time pressure and work quality was found by Kelly and Karau (1999), and Andrews and Farris (1972) also found a positive long-run effect of time pressure on creativity. In more recent related work, Amabile et al. (2002) (as well as Amabile, Hadley, and Kramer, 2002), using a novel daily electronic questionnaire collected over 30 weeks from 177 individuals in seven companies, found a negative effect of higher time pressure on creativity. Thus, how time pressure affects work quality remains an important, yet open empirical question.

Our setting allows us to address this question in an extensively large sample context utilizing various measures of different dimensions of work quality. Our results suggest that increased time pressure close to deadlines does indeed have negative effects on work quality. These quality results are robust to numerous alternative tests (including using different sample periods and industry sub-samples, as discussed in Section 6). Thus, across thousands of different firms over a fairly long time period, we find robust evidence for negative quality effects of time pressure, consistent with findings in some of the prior studies on time pressure (Amabile et al., 2002; Kelly and McGrath, 1985), but contrary to the positive effect found in other studies (Andrews and Farris, 1972; Kelly and Karau, 1999) and the null effect in Basett (1979).

Finally, our work contributes to the literature on innovation, by focusing attention on the relatively understudied application preparation part of the patenting process. Our work draws on and contributes to the smaller literature that uses information in the patent application/approval data to uncover underlying important features of the innovation and patenting process (Alcacer and Gittelman, 2006; Alcacer, Gittelman, and

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As Bluedorn and Denhardt (1988) note, the idea that time pressure could have a positive effect on decision making goes back to at least March and Simon (1958, pp. 116, 154) who suggested that as time pressure increases, the search for alternatives will become more vigorous and selective perception will increase. Kelly and Karau (1999) propose an attentional focus model for group work, which suggests that time pressure could either enhance or reduce performance depending on requirements of the task and environmental cues. In particular, time pressure could enhance performance by leading groups to focus on the appropriate amount of information that is truly relevant and diagnostic. Consistent with this model, Kelly and Karau (1999) find evidence suggesting that time pressure improved task focus and reduced interpersonal and other activities that did not advance the task.

A strand of literature in political science has examined the effect of deadlines on the performance of government agencies (Abbott, 1987; Carpenter et al., 2008, 2012; Gersen and O’Connell, 2008). Gersen and O’Connell (2008) point out that deadlines allow legislatures to control agencies – specifically by influencing the allocation of resources to specific tasks within specific time frames – while allowing the agencies that arguably have better information and expertise to make decisions based on their discretion. At the same time, deadlines may not be imposed optimally, which could lead to a misallocation of resources within agencies (or even lowering of work quality, as argued earlier by Abbott (1987)).

We want to note that, our findings, and those in the literature, do not rule out a non-linear (inverted-U shaped) relationship between time pressure and work quality. In particular, our findings are consistent with the extent of time pressure from the deadlines in the data being on the downward portion of the inverted-U shape. Our findings are also consistent with those in Carpenter et al. (2008, 2012), who find that new deadlines imposed on the Food and Drug Administration (FDA) for certain drug reviews led to clumping of approvals near deadline dates and significant declines of decision quality (e.g., more recalls, more labeling revisions) for applications approved close to the deadline.

2 Theoretical Motivation

We develop a formal mathematical model to motivate drivers and impacts of deadlines. Given the focus of this paper, however, we discuss the underlying intuition here, leaving the technical derivations to the Appendix.

The key elements of the model are summarized in Figure 1. Briefly, the model focuses on lawyers involved in the drafting, finalization, and filing of applications, as agents of a principal. The ultimate principal is the management of the inventing firm, but if the filing is completed by an external law firm, the partners of that firm also serve as a principal monitoring the attorney working on the filing. The agents complete tasks (that is, they file applications), possibly of varying “complexities,” that arrive randomly and independently over time. The optimal time taken to complete a given task depends on the costs and the benefits to the agent from completing that task. These costs and benefits both increase, albeit at different rates, with “complexity” of the tasks but decrease with time spent on the task.\(^{11}\)

These agents face time pressure due to deadlines. Deadlines, which arise from considerations (left panel of Figure 1) described below, are defined as periodically occurring checkpoints when the agent faces a penalty for having incomplete tasks. This penalty is usually imposed directly by the principal—for instance, as lower performance evaluations or monetary incentives—but it can also be indirect, such as peer pressure associated with not meeting deadlines.\(^{12}\) We then analyze how agents respond to the deadline penalties, and study if that causes clustering of work flows, if they choose to accelerate some tasks more than others (“task sorting”) depending on the complexity of the tasks, and the effect on observed work quality.

Need for Deadlines

In the context of our model, deadlines address the incongruity between the principal and agent with regard to the benefits and costs associated with adjusting the speed of completing a task. In general, as is well understood, the principal can try to align the agent’s interests with theirs through suitably designed incentives. For instance, they can use performance measures to set bonuses, raises, or promotions for the attorneys who are undertaking the application work (e.g., Lazear and Gibbs, 2014, Ch. 9). However, as is also well known, there are numerous challenges to measuring performance and rewarding agents (e.g., Lazear and Gibbs, 2014, Ch. 9 and 10), so that even with a well-designed performance evaluation and incentive system, the perceived benefit and cost trade-offs from accelerating may not be the same for the principal and agent.

There are three key sources for such inconsistencies in our context. First, managers at the inventing firm (e.g., R&D managers) may have planning, reporting, and coordination considerations, which are not directly perceived by the attorneys. So the managers may require at least some subset of applications to be completed

\(^{11}\)Throughout the paper, we use the term “complexity” in a very specific sense. In the model, the term “complexity” means a characteristic of an application such that: (i) the benefits of filing a more “complex” application are higher than the benefits of filing a less “complex” application, and (ii) the costs of filing, including the cost of errors, are higher for more “complex” applications than for less “complex” applications. It is in this sense that we use the term in this paper. This term then encompasses not just complex and technically challenging/novel applications, but also important (even if simple) applications, as conditions (i) and (ii) are likely to apply to the latter as well. The Appendix to this paper provides a more a detailed discussion of this point.

\(^{12}\)Section 6.1 discusses evidence from our attorney surveys consistent with this assertion.
faster than what the attorneys would like to complete them in, leading the firm to impose deadlines. Second, principals may perceive a greater benefit from earlier filing than that perceived by the agent. For example, firms in more technologically competitive industries (i.e., with shorter cycle times) may wish to accelerate applications more than for the average firm across all sectors, which may not be internalized by the attorney working on the patent. Third, the partners of an external law firm may want to reduce working capital needs by minimizing un-billed balances. These working capital costs of unbilled hours may not directly enter the objective function for the attorney; then the benefit from accelerating seen by the principal is different from that perceived by the agent.

There may be additional sources of inconsistencies. For instance, the principal and agent may differ in the perceived opportunity cost of the agent’s time (e.g., in terms of the importance of other tasks they need to work on, as in Holmstrom and Milgrom, 1991). Furthermore, procrastination tendencies (e.g., as discussed in Cadena et al., 2011) could lead the agents to delay completion of tasks, arising because the agents view the short-term costs of finishing the tasks as more salient than the benefits (e.g., O’Donaghe and Rabin, 2001).\(^{13}\) Taken together, these arguments imply that the principal is often likely to have a shorter optimal time for completing the task than the agent. In such a case, as shown in Appendix A, it follows that imposing a deadline-related penalty will increase the principal’s payoff.

**Impact of Deadlines**

When faced with a deadline penalty, agents weigh the cost of accelerating their task to meet the deadline with the benefits of such acceleration. For the agent, the key benefit of meeting the deadline is avoiding any deadline-related penalties. For instance, in our survey of attorneys, nearly 75% of the respondents said lower performance evaluation was a potential cost of missing a deadline, “sometime or more often” (see Online Appendix S2). Sixty percent said the same for pressure regarding unbilled hours. The potential loss of repeat business due to client dissatisfaction or a damaged reputation is also a major cost, particularly for external attorneys.\(^{14}\)

However, the agent also faces costs associated with accelerating task completion. An important cost is the opportunity cost of the additional time the agent has to spend before the deadline completing the task (e.g., the agent may have to work late or over weekends). Another important cost relates to additional errors in the application due to rushing. In the worst-case scenario, the application may be fatally flawed, resulting in it being rejected entirely by the USPTO or a loss of priority date. However, given the reputation costs at stake for the agent, our interview and survey evidence suggest that is not very likely. More likely, though, are errors that lead to lack of clarity in the wording or cause additional transactions during the patent prosecution (review) process. Eight-four percent of our respondents cited lack of clarity in the “specification” (that is, the description of the invention being patented) as being a risk associated with rushing an application,\(^{13}\)

\(^{13}\)Our principal-agent framework for motivating deadlines is consistent with the approach in ODonaghe and Rabin, 2001, who focus on deadlines as a way to combat inefficiency from time-inconsistent procrastinating behavior by agents. However, they note that, “Clearly, there are many reasons for deadlines other than combating procrastination. A major one, intuitively, is coordination among agents: in an organization it is often useful to know a date by which a project is intended to be complete. A second potential reason for deadlines is their simplicity: it may be easier to monitor whether somebody has met or missed a deadline than to monitor exactly when a project was completed.” Our parsimonious framework nests procrastination among a list of other sources of incongruity between the principal and the agent.

\(^{14}\)See Section 3.2 for more detail on our surveys.
“sometime or more often.” Not surprisingly, nearly 65% of survey respondents rated the cost of an unclear specification—the loss of some claims—as a risk of rushing. Other risks include inadequate prior art disclosure and additional work and filing fees. Even though these costs are eventually borne by the inventing firm, they are passed to the agents, and hence affect their decision to (or not to) accelerate task completion.

Given the costs and benefits of task acceleration, we show that agents accelerate some tasks that would otherwise be completed “just after” the deadline, so that those tasks are completed at the deadline. To see the intuition, if a task would be completed on Apr 3 without acceleration, agents may complete it on Mar 31 if they face a modest deadline penalty. However, they are less likely to accelerate (to Mar 31) a task of the same complexity if it would normally be completed only on Apr 27. A much higher deadline penalty would be required to achieve that. Also, since there is no incentive to complete earlier than the deadline, all these accelerated tasks are completed at the deadline. Thus, it follows that:

**Hypothesis 1:** In the presence of a deadline penalty, there is clustering of task completions at the period-end deadline.

Agents will not accelerate all tasks equally. In particular, more-complex tasks are likely to take longer to complete and are likely to have a higher error rate. Hence, accelerating such tasks may be more costly for the agents. On the other hand, more-complex tasks are also likely to have greater deadline-related penalties than less complex ones. For instance, unbilled balances on a 90-day task that is scheduled to end on April 3 has an 87-day unbilled balance on March 31, while a 30-day task has only a 27-day unbilled balance. Hence, the law firm partner may be more motivated to accelerate billing on the larger tasks. Similarly, the management of an inventing firm may care more about more valuable patents, and impose greater penalties (or may be more likely to impose penalties) for not completing the associated filing by the deadline. Also, if the incongruity arises from behavioral biases, agents may be more likely to procrastinate for complex tasks (O’Donaghue and Rabin, 2001). Hence, whether more or less complex tasks are chosen for acceleration depends on how complexity affects the costs of accelerating and the penalty of being incomplete at the deadline. This leads to the following proposition.\(^{15}\)

**Hypothesis 2:** Under some conditions, the average complexity will be higher for tasks completed at the deadline.

As discussed in the introduction, the theoretical literature on the impact of time pressure on work quality is ambiguous, and potentially suggests an inverted-U-shaped relationship. On one hand, time pressure may improve performance by increasing search intensity, as suggested by March and Simon (1958, pp. 116, 154), or by narrowing attention on task-completion-focused activities (Karau and Kelly, 1992; Parks and Cowlin, 1995). On the other hand, having too little time could reduce performance quality (especially for complex tasks) by restricting the amount of information considered or the thoroughness with which information is evaluated (Kelly and Karau, 1999).

In our model, deadlines affect average work quality in two ways. First, conditional on quality, accelerating tasks unambiguously increases the error rate (our error function has an inverse square dependence

\(^{15}\)The conditions under which more complex tasks get accelerated conditions are set out formally in the Appendix; essentially, the difference between the marginal effect of complexity on the error rate and that on the deadline penalty needs to be low enough. To see the intuition, note that for example, if the deadline penalty were (sufficiently) stronger for less complex patents, then in fact agents would be induced to accelerate the least complex patents.
on task duration). But a second, subtler effect kicks in due to task sorting, so that the equilibrium average error rate for accelerated tasks is ambiguous. In particular, if the marginal error cost is high relative to the marginal benefit from speeding, the duration choice will be high enough that the error rate is lower for morecomplex tasks. Then, because more-complex tasks get sorted to month-ends, unconditional on quality, the error rate could be lower for the month-end. Hence, it follows that:

**Hypothesis 3a:** If the marginal effect of complexity on the error rate is low enough (relative to the marginal effect on gains from acceleration), average work quality is lower for tasks completed at the deadline.

**Hypothesis 3b:** For any given task complexity, work quality is lower for tasks completed at the deadline.

From a principal’s point of view, though deadlines enable faster task completion, they are also likely to have fixed costs associated with monitoring performance relative to the deadlines. Hence, large firms with sufficient volumes are more likely to find it beneficial to use deadlines to motivate earlier patent filings. Furthermore, coordination considerations are likely to be more important in large firms, which further increases their incentive to use deadlines.

Technology characteristics may also affect the prevalence and severity of deadline penalties. Specifically, technologies vary in the speed of innovation; some technologies change slowly, while others change rapidly. As one of our interviewees stated “... pharma firms want every day of [the] patent term... computer tech[ology] change[s] very quickly, so, computer companies do not really worry that much about full term.” Not surprisingly, this speed of change will directly affect the deadline-related incentives faced by firms and their attorneys. In particular, the incentive to file early increases in areas where technological change is rapid, as the risk of being scooped by a rival is higher. Therefore, deadlines are likely to be more pervasive or more stringent, and consequently, complexity and quality effects at month-ends are likely to be stronger in sectors with shorter cycle times. In particular, firms are more likely to file earlier in technologies that are changing rapidly, so that they can maintain an advantage over their rivals. This, in turn, increases the benefit of using deadlines to motivate earlier filings. Taken together, it follows that:

**Hypothesis 4:** The impact of deadlines will be greater for larger firms and in sectors with a more rapid pace of technological innovation.

### 3 Data

We use (i) secondary data from various datasets and (ii) primary data from surveys and interviews of practitioners.

#### 3.1 Datasets

The primary source of our patent data is the USPTO. We purchased data on all utility patents granted between January 1976 and August 2009 (a total of 3,209,376 patents). This data included the patent number, U.S. classes and subclasses, the number of claims, and application year of each patent, as well as citations to a patent. For most of our analysis, we use only data on patents assigned to “organizations,” identified by assignee codes “2” and “3.” We excluded patents assigned to universities and multiple assignees, and

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16 We thank the Associate Editor and three anonymous reviewers for pointing us in this direction.
eliminated patents that were not applied on a USPTO working day (0.6% of patents). We supplemented these data with the NBER Patent Data (2009), an updated version of Hall, Jaffe, and Trajtenberg (2001). This dataset provides dynamic matching between the firm name in Compustat and the assignee name in the USPTO patent data for the period 1976–2006. To assign ownership after 2006, we used the assignee names and identifiers from the USPTO data, and assumed that ownership of assignees did not change after 2006. If a new assignee was observed in the USPTO data after 2006, it was treated as a new firm.

We also used application data that include successful and unsuccessful patent applications, purchased from Fairview Research LLC. The data include information on all U.S. Pre-Grant Applications published by the USPTO between January 1, 2001, and December 31, 2010. In addition to the application filing date and application number, the database includes application type (utility or design), number of claims, publication type, and importantly (to control for firm fixed effects), standardized assignee names. To merge the application data with other patent databases, we did some further standardization of the assignee names (code available on request).

To examine potential differences in work quality, we collected the transaction history of patent applications from Google Patents. The USPTO records every administrative action associated with each patent application, starting with the initial exam team assignment to the final grant or abandonment, which enables a detailed tracing of the review process for each application. To allow for sufficient time between filing and the final decision, we limited our sample to applications filed by U.S. firms during 2001–2004. As of January 2012, about 52% of the applications were available for download. Even with this subset, downloading entire documents posed technical challenges, as many of the files were very large in size. Trading off these challenges against diminishing benefits of increasing sample size, we downloaded a 25% random sample of the available applications.

To these, we added data on patent attorneys from the Patent Network Dataverse (Lai, D’Amour, and Fleming 2009) and data on examiner-added citations from Sampat (2012). Lai et al. also disambiguate the names of inventors and assign a unique identifier to each inventor that appears in patents granted between 1975 and 2008. In a robustness check, we use this information to control for inventor-level heterogeneity by using inventor-specific fixed effects. The various samples used in the main analyses are presented in Table B2 of the Online Appendix.

### 3.2 Surveys and Interviews

We supplemented the above data with information from three surveys and 21 interviews with practitioners (inventors and attorneys) who had extensive firsthand experience in filing patent applications. Our first survey (“Inventor survey”) focused on inventors and attempted to understand their role in the patent application process. Specifically, we administered a survey to global alumni of a globally known science and technology...
tical institute based in India, who were working in R&D departments, primarily as inventors. We obtained about 140 complete responses to our survey. Additional details are provided in Online Appendix S1. The second survey (“Law firm patent attorney survey”) was administered to patent attorneys at law firms, and received about 50 complete responses. The third survey (“Corporate patent attorney survey”) was administered to patent attorneys at inventing firms, and received about 13 complete responses. In addition to getting their opinion on the observed clustering of filings, these two surveys aimed to understand the incentives and penalties faced by patent attorneys in the patent filing and prosecution process. Details on these two attorney surveys are provided in online appendices S2 and S3, respectively.

In addition to these surveys, we conducted in-depth interviews with practitioners. The objective was to obtain detailed information on the patenting process inside firms, as well as to gain insights on the observed clustering of patent applications. The list of interviewees included: (i) legal staff (mostly IP attorneys) at seven large patent-intensive firms, (ii) legal staff from nine independent IP law firms, and (iii) four inventors, each of whom had multiple inventions patented at different global electronics and semiconductor firms. The interviews, conducted either via phone or in person, lasted from a minimum of 20 minutes to a maximum of two hours. All of these interviews were semi-structured; we first asked the interviewee several standardized questions based on our observations and then opened the conversation to unstructured responses. A summary of responses from the interviewees as they relate to our study are discussed in Section 6.1. Because we promised respondents confidentiality, names of respondents and individual firms are kept anonymous.

4 Empirical Analysis

4.1 Deadlines and Work Flow Clustering

Figure 2 plots each calendar day’s average share of granted applications (for the period 1976 to 2009) for corporates and individuals, and the difference in day-shares between corporates and individuals. The vertical lines denote month-ends. The figure shows a substantial upward spike in filings at the end of every month for corporates, but no spikes for individuals (except for September-end, which corresponds to the year-end for the USPTO, with a potential for an increase in fees beyond this date). For corporates, September and June show the highest month-end spikes, while the clustering is somewhat muted for May, November, and December, all of which have a U.S. holiday at the end of the month.21 We combine these two in the bottom row, which plots the difference in day-shares between corporates and individuals, and confirms that the clustering is much stronger for corporates, consistent with the patterns arising from periodic routines and associated deadlines.

To formally test for differences between corporates and individuals, we present in Table 1 results from the following regression specification: \[ y_d = \beta_1 D_{1-7} + \beta_2 D_{8-15} + \beta_3 D_{16-23} + \beta_4 D_k + \epsilon_d \], where \( D_k \), \( k \in 1, 3, 5 \) indicates a dummy variable for the last \( k \) days of the month, and \( D_{m-n} \) is a dummy variable for days \( m \) to \( n \) of the month. The dependent variable in columns 1 to 3 of are day-shares for corporates defined for day \( d \), \[ s^F_d = \frac{\sum_{t=1976}^{2009} n^F_{dt}}{\sum_{t=1976}^{2009} n^F_t} \] where \( n^F_{dt} \) is the number of successful patents (or published applications) applied by

21 Memorial Day in May, Thanksgiving Day in November, and Christmas in December. The four downward spikes correspond to 1/1, 2/29, 7/4 (U.S. Independence Day), 11/11 (Veterans Day in the U.S.), and 12/25.
corporates in day $d$ of year $t$, and $n^F_t$ is the number of successful patents (or published applications) applied by corporates in year $t$. In columns 4 to 6, the dependent variable is $\pi^I_t$ is defined similarly for individuals.

We see strong clustering of filing in the last few days of the month for corporates (columns 1 to 3), whereas the clustering is much more muted for individuals (columns 4 to 6). For readability, all coefficients and standard errors in this and other tables have been scaled by 1,000. The month-end effects are clearest when looking at the differences between the month-end dummy and the dummy for days 1–7 (in row 7 of Table 1); this shows that for corporates the share of filings in the last day of the months are about 0.09 percentage points (column 1) more than that for an average day in the first week of the month, while the same difference is only 0.028 percentage points for individuals (column 5), so that there is excess clustering for corporates (relative to individuals) of about 0.065 percentage points (column 7). This effect is significant in magnitude, considering that if patent filing patterns were uniform throughout the year, we would expect 0.27% (1/366) of annual patents on any given day for both individual inventors and firms. Thus, the excess month-end filing share is about 23.6% of the expected uniform filing rate.

Together, these results strongly support Hypothesis 1. In Section 6.1, we discuss direct evidence from extensive primary data collection efforts, as well as results from a battery of additional statistical tests, that strengthen the conclusion that deadlines associated with various corporate organizational routines are driving the observed month-end clustering patterns.

4.2 Deadlines and Task Complexity

Recall that in our model, complexity has the following characteristics: the benefits for completing more-complex tasks earlier are higher, and the cost of errors is higher for more-complex tasks, so that more time (intuitively, more effort) is required to complete a more “complex” task. In our empirical analyses, we examine six different observed variables that are likely to be correlated with the complexity of an application in the aforementioned sense. Specifically, we use the number of claims (available for both patent and application data), the number of drawings, the number of drawing sheets, and the number of drawings per drawing sheets (all available only in the patent data) as measures of complexity. Applications with more claims and drawings are likely to take longer to complete and often result in higher fees for attorneys (70% of our attorneys in our surveys said their fees depend on these variables; see Question 11, Online Appendix S2). In addition, we used the number of citations to a patent within the five years from its application date and the probability of renewal at 3.5 years after the grant as additional measures. Though these measures are considered a proxy for patent value (e.g., Hall, Jaffe, and Trajtenberg 2005; Pakes 1986), more valuable patents are likely to involve more care and hence more effort in drafting the application, greater benefits to completing the application, and higher costs of any errors. Hence, citations and renewal are likely to indirectly reflect the deadline-related trade-offs being studied here.

Before we present formal regression estimates, we show results for three of the measures in the top panel of Figure 3. Across three key measures of complexity, there is a sharp increase toward the end of the month; patents or applications filed close to month-ends contain more claims, are cited more frequently, and are more likely to be renewed. We test the significance of this pattern for all six of our measures using the following specification:

$$C_{pjtm} = \beta_D.D_{pjtm}^k + \alpha.y_{jt} + \tau_t + \nu_m + f_j + \tilde{\epsilon}_{pjtm}$$  \hspace{1cm} (1)
where $D_{pjtm}^k$ is a dummy defined earlier for the last $k$ working days of the month, $C_{pjtm}$ is a measure of complexity, $y$ is a measure of firm size defined as the number of patents (or applications) belonging to firm $j$ that were applied in year $t$, $\tau_t$ and $\nu_m$ are application year and application month fixed effects, and $f_j$ denotes firm fixed effects.

For brevity, only the coefficients on the month-end dummy are presented in Table 2. The number of claims is significantly larger for month-end applications: 0.9% larger for applications filed in the last three days of the month, and 1.7% larger for those filed on the last working day. Similarly, the number of drawings and drawing sheets are higher by about 1.2% and 1.4%, respectively, for applications filed on the last working day of a month. Consistent with more-complex drawings being larger, the number of drawings per drawing sheet is lower by about 1.1% for applications filed on the last working day of the month. The two indirect measures of complexity also show a similar pattern. The five-year citation count is greater for month-end patents: the citation count is about 1.5% higher for patents filed in the last working day of the month. Month-end patents are also more likely to be renewed, by about 0.2%. Together, these tests strongly confirm Hypothesis 2, that applications of higher complexity are more prone to be completed toward month-ends.

4.3 Deadlines and Work Quality
We measure work quality of a patent application using two types of measures: (i) errors and additional work needed during the patent prosecution process (“work process-based measures”) and (ii) the quality of outcomes associated with the application (“work outcome-based measures”). With regard to the former, we rely on specific transactions that occurred during the prosecution. For instance, the USPTO sends an “Application Incomplete” notice if the application is missing some documents, and records “Additional Application Filing Fees” if the applicant had to pay such fees at some point during the prosecution (typically due to delays in filing documents). Specifically, we included the following in the first group of measures: (i) application incomplete notice—filing date assigned; (ii) a statement by one or more inventors satisfying the requirement under 35 USC 115, oath of the applicant, is missing; (iii) additional application filing fees; (iv) new or additional drawing filed; (v) information disclosure statement (IDS) filed after the initial filing date; (vi) non-final rejection; (vii) request for extension of time - granted; and, (viii) restriction/election requirement.22

We identified six of these transactions based on the list of transactions that appear in the data, and independently confirmed their validity through interviews with three different practicing patent attorneys. One of these measures (non-final rejection) was suggested by an anonymous reviewer. The last measure (IDS filed after the initial filing date) was added based on the suggestion of an interviewee. In addition, we performed a factor analysis (PCA with varimax rotation) of these measures and identified a single factor (eigenvalue 2.23 vs. 0.53 for the next factor), which we added as another measure of process-based work quality. The practitioners confirmed that all of these measures are more likely to occur if the filing is rushed, and hence can be considered good indicators of a poorly prepared application. Although they are unlikely to result in the loss of a priority date, these transactions require rework and re-filing by the attorneys, and hence impose costs on the filing firm. Our interviewees indicated that the extra time and effort to

22For readers unfamiliar with these terms, a glossary in the Online Appendix describes them.
address some of these transactions could be a sizable fraction of the cost of the initial application. For instance, one respondent indicated that his firm charges around $3,000 to $5,000 for each re-filing involving minor changes, and from $5,000 to $10,000 for those involving more-complicated responses. This is very significant compared with the $10,000 to $15,000 the firm charges for the original application filing. Another indicated that they charge about $2,500 to respond to a typical non-final rejection, which is a sizable fraction of their initial filing expenses of $6,500-$10,000. In addition to attorney effort, the USPTO also charges late fees and additional filing fees in many of these transactions, though they tend to be smaller in magnitude. From the attorneys’ perspective, our surveys indicated that many of these transactions are viewed negatively by clients (Table S2E). Hence, the occurrence of these transactions results in costs to the attorneys as well. Thus, in general, it is in the best interests of the inventing firm and its attorneys to ensure that the application is as well prepared as possible.

In addition to these eight work process measures, we chose three measures that are more closely related to the outcome of the work: (i) the share of citations added by examiners, (ii) application success, and (iii) log review time. The share of citations added examiners, suggested by an anonymous reviewer, reflects the extent of prior art disclosure in the initial filing. Poorly prepared applications may tend to have fewer citations to prior art, requiring the examiner to add some of his or her own during the prosecution (examination) process. Application success is an indicator of whether the application resulted in a patent or not, and is a reflection of the overall outcome of the task (i.e., the filing of the application). Finally, the review time is also reflective of the overall outcome, though it can also be viewed as an indicator of the overall process quality.

As one of our interviewees put it, “I see a longer approval time as being costly to a company... [in that the company] has incurred the cost having to file multiple replies in that time instead of getting it quickly granted. . . .[h]aving a granted patent in hand is required for that company to file a patent infringement lawsuit against [a] competitor, and provides much more leverage for the company... in possible settlement or licensing negotiations with that competitor.”

To examine whether month-end applications are more likely to have a lower work quality (Hypothesis 3a), we estimate a regression model similar to that in Equation 1, except that the dependent variable is $q_{pjtm}$, a measure of work quality. For each of the eight work process measures, it is defined as 1 if the transaction history of that application contained that transaction and 0 otherwise. Application success was defined similarly depending on whether the application resulted in a patent or not. For the other two outcome measures, we used the actual values as the dependent variable. To test Hypothesis 3b, we add log number of claims as a control.

Table 3 presents the coefficients on the month-end dummy. They are positive and significant for all work process measures. Hence, month-end applications are much more likely to encounter these transactions than other applications. Specifically, applications filed on the last working day of the month are 4.6% more likely to receive an incomplete notice from the USPTO. The corresponding numbers for the last three and five working days of the month are 3.6% and 3.0%, respectively. Given that only 29% of applications in the sample receive such a notice, these differences are substantial (a 15.8%, 12.4%, and 10.3% higher

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23 Because disclosing prior art limits the scope of the patent being requested, there is an incentive for the firm to minimize the extent of disclosure, which implies better-prepared applications could in fact have a greater share of examiner-added citations. In the presence of such behavior, our results using this variable will then overestimate error due to rushing.
probability relative to the baseline rate). Similarly, applications filed on the last working day are about 4.9% more likely to submit the inventor oaths separately, 4.7% more likely to pay additional filing fees, 1.5% more likely to submit an additional drawing, and 2.2% more likely to file an information disclosure statement after the initial filing. Compared with the respective baseline rates of these transactions, these are significant (18.6%, 14.8%, 11.0%, and 3.7% higher than their respective baseline rates). The effects for the other three measures are similar: 2.3% higher probability relative to the baseline for a non-final rejection, 4.8% higher for a request for extension of time, and 12.9% higher for a restriction requirement.

Turning to the work outcome measures, the effects are in the same direction as the process measures but are more modest in magnitude. Compared with the mean, applications filed at month-ends have a 4.3–6.9% greater share of examiner added citations, take about 0.9–2.2% longer to review, and are about 0.1–0.5% less likely to be approved.

Columns 5 to 8 repeat the analysis conditioning on complexity (measured as log number of claims); consistent with Hypothesis 3b, we find lower month-end work quality in this case also.

The bottom panel of Figure 3 presents a subset of these results in a graphical format. Specifically, the figures present a predicted fractional polynomial fit of the residuals of the dependent variable (de-meaned of firm fixed effects) on working day of the month. It is clear from the figures that there is a discernible change in work quality as we move from the first working day of a month to the last. The magnitude of the differences is similar to that documented in Table 3.

Together, these results clearly support Hypotheses 3a and 3b, and strongly suggest that the work quality of the applications completed on the last few days of the month is distinctly lower. Interestingly, the effect on the immediate work process is larger than on the longer-term work outcomes, which is consistent with firms expending additional effort on addressing errors in month-end applications during the prosecution process in order to avoid longer-term negative outcomes.

4.4 Heterogeneity in the Deadline Effects

Hypothesis 4 relates clustering patterns to heterogeneity in size across firms (with larger firms more likely to incur fixed costs associated with deadline routines) and speed of technology change across industries (with sectors with shorter technology cycle time more likely to provide incentives for rushing by using deadlines).

Size-related Heterogeneity. The first row of Table 4 (columns 1 to 3) presents the coefficients on log firm-year size (columns 1-4) from a regression of a month-end dummy (D1, D3, or D5) on these variables, and application year and month fixed effects. The positive and strongly statistically significant coefficient in all three cases reveals that clustering is indeed strongly positively correlated with firm size. In the rest of the rows, we regress measures of work complexity and quality on an interaction of the month-end dummy with firm-year size, the corresponding direct terms, and application year and month fixed effects. Work complexity, as measured by claims and citations, at month-ends shows a strong positive correlation with firm size. Similarly, work process quality at month-ends is also distinctly lower for larger firms. We do not find any strong interaction effects on the work outcome measures, perhaps due to the larger resources available to large firms to address errors in the work process. Taken together, our results support the use (and/or intensity) of month-end deadlines increasing in firm size.

Speed of Technological Change-related Heterogeneity. We adopt the same approach as above, except
that we use “technology cycle time” (instead of firm size), defined as the mean time gap between a patent application and its backward citations. This measure has been used in the literature to represent the speed of technological changes in a field (e.g., Balasubramanian and Lee, 2008). The results, presented in columns 5 to 7 of Table 4, show that technology cycle time is indeed significantly negatively correlated with month-end clustering (row 1). This strongly supports our hypothesis that technologies with shorter lead times are more likely to exhibit clustering. Results in rows 2 to 4 show that, consistent with our hypothesis, complexity by all three measures (claims, citations, and renewal probability) for month-end filings appears to be negatively correlated with cycle time (though the results are not statistically significant for renewal probability).

Rows 5–10 also reveal that work quality reduction is more modest in industries with longer cycle times (or equivalently that work quality at month-ends is relatively worse in industries with faster innovation), consistent with our hypothesis. Taken together, these results are consistent with the speed of innovation increasing the incentive to engage in rushing behavior.

Because the expected sources of heterogeneity are related to the expected pervasiveness or stringency of deadline penalties, the consistency of the results for clustering with those for complexity and quality provides strong additional evidence that all of the effects — greater clustering, higher task complexity, and lower work quality at month-ends — are indeed driven by month-end deadlines.24

5 Benefits from Rushing: Insights from a Calibration Exercise

Our empirical analysis shows degradation of work quality associated with rushing around deadlines. However, as discussed in our theoretical framework (and related model in the Appendix), the principal may reap offsetting benefits from the acceleration of work. Since the data do not allow us to directly observe potential benefits of rushing, we adopt an alternative approach by calibrating the theoretical model to our data. This allows us to estimate two sources of benefits: days saved, and days of un-billed balances saved, and undertake counterfactual exercises altering both the strength of, and the intervals between, the deadline penalty.

To calibrate, we impose additional structure on the baseline model (details in Online Appendix) and calibrate our \( \gamma \) parameter (which proxies intensity of the deadline penalty) to a value that yields a last-day share equal to that in our sample of applications. We standardize this value of \( \gamma \) to be \( \gamma_s = 1 \). In the Online Appendix, we show that our calibration replicates the empirical results well. Next, we estimate the same penalty parameter (\( \gamma_s \)) for each of the top 200 patenting firms in our sample so that the last-day share from the model matches the average last day share for each of these firms within a tolerance of 0.005%, subject to \( \gamma > 0 \). We then use Lowess smoothing to non-parametrically map the associated model predictions regarding additional error at the month-end to the actual mean additional error rates (as measured by propensity for “Application Incomplete” notices) of these firms. This mapping, along with the set of \( \gamma_s \), forms the basis for our exercise.

Table 5 presents the results of our counterfactual analyses. Unless stated otherwise, the table presents standardized values to make comparison across different scenarios meaningful. We present four statistics for each scenario: the standardized period-end share (i.e., the percentage of period-end filings that are ac-

24For instance, if month-end clustering is driven simply by mental accounting deadlines set by individuals, that would not explain the stronger effects for large firms, or in more technologically innovative industries.
celerated), the percentage error differential, the percentage duration reduction, and the percentage reduction in days of unbilled balances for accelerated tasks relative to other filings. Our analysis confirms that, not surprisingly, the extent of clustering increases as the deadline-related penalty costs increase. Increasing the length of the deadline period beyond a month does not seem to significantly change the share of period-end filings that are rushed or improve the error rate of period-end applications (though this does impact the share of total patents that get rushed, and consequently the overall average error rate).

Focusing on task acceleration, an aspect that cannot be directly observed from the data even for the baseline case, the calibrated model suggests that the average task acceleration of rushed tasks in the sample is about 1.5 days, or about 1.8% of the time taken to complete the task, were it not accelerated. The extent of acceleration, though increasing in penalty costs, remains small across all the scenarios. Even in the high-penalty scenario, acceleration of rushed tasks is never more than 2.2%. Hence, our calibration exercise suggests that benefits in workdays saved from task acceleration is fairly small.

However, even the small acceleration in duration leads to substantial savings in working capital (days of unbilled balances), as this pushes accelerated jobs to be billed one full cycle earlier than they would be otherwise. Another key result is that the working capital savings move proportionately with the deadline intervals (assumed here to be the billing cycle length). This is because, for a job that gets completed just after a billing deadline, the working capital costs are larger if the billing intervals are longer. The counterfactual simulations show that gains (from working capital savings) are muted, and costs (from errors) are larger when the billing intervals are shorter, so that smaller penalties are likely to be more optimal when inter-billing intervals are shorter.

6 Robustness Checks
6.1 Are the Clustering Patterns due to Deadlines?
Here, we present evidence from our primary data and additional empirical analyses to reinforce the conclusion in Section 4.1 that clustering patterns are caused by deadlines.

Evidence from interviews and surveys of practitioners. The most direct support for the observed clustering being due to deadlines comes directly from our surveys and interviews of practitioners. When asked about the possible reasons for the observed clustering, not a single one of the 64 respondents in our attorney surveys chose a non-deadline related reason. Also, every one of the 16 interviewees attributed the observed clustering to organizational deadlines. As one interviewee said, “The most likely thing that could be driving these results is law firm internal revenue issues...” Another attorney remarked, “There may be a lot of pressure on attorneys at law firms to bill out any billable work for that month. So, they may have a motivation to complete work by the month-end so they can invoice the clients for it. [Also], ... many inventing firms (especially the larger, sophisticated ones), are likely to have metrics and cyclical reports (monthly, 25 26 The intuition for the baseline unbilled balance acceleration in Table 5 of about 30% is as follows: in the baseline scenario, our calibration suggests that tasks of mean duration of about 96 days are accelerated by about 1.7 days (yielding the 1.8% acceleration). This small acceleration causes rushed tasks to get billed one billing cycle earlier than otherwise, yielding a saving of about 20.3 days (22 – 1.7), which in percentage terms is about a 30% reduction (20.3/22). Because the acceleration is tilted toward longer duration tasks, the savings in level terms are even more than they would be otherwise.
Consistent with this, in our inventor survey, we find a positive correlation between the pattern of monthly clustering and the reporting deadlines for external attorneys. Specifically, Figure S1A and Table S1E show that organizational clustering patterns correspond exactly with the reported deadlines (annual deadline firms show year-end, quarterly deadline firms show quarterly, and monthly deadline firms show monthly clustering). Additional evidence comes from our law firm attorney surveys. We compared filing patterns for firms whose respondents cited monthly billing cycles as a possible reason for the clustering to filing patterns for firms who did not mention these cycles as a reason. Figure S2B shows that those who mentioned monthly billing cycles (indicated by a solid blue line) are more likely to exhibit month-end clustering.

Our surveys also indicate that patent attorneys face significant costs if they do not meet a deadline. Nearly three-quarters of all respondents said that missing a deadline is likely to lead to lower performance evaluations sometimes or more often (Table S2D). More than a third rated such a possibility as often or higher. Related qualitative comments on possible consequences of missing a deadline also pointed to such costs (e.g., reduction in available work, unhappy client, and payment for loss or damages). We performed a more formal analysis of whether these perceptions of costs are associated with month-end clustering. We defined a dummy variable costlymiss as one if the respondent rated any of the three aforementioned consequences as sometimes or higher. We then plotted the month-end share of filings for these two groups of patents. The results presented in Figure S2D clearly indicate a much higher prevalence of month-end clustering among the group that rated the consequences as more likely (solid line represents costlymiss = 1). This supports a direct association between the disincentives related to missing deadlines and month-end clustering.

Our respondents also provided their opinion on the negative perceptions associated with several transactions during the patent prosecution process. We created a dummy variable, negpercep, defined as one if the respondent rated the occurrence of any of four transactions (application incomplete, request for extension of time, new drawings to be filed, additional filing fees) as somewhat negative or worse. We then plotted the month-end share of filings for these two groups of patents. The results clearly indicate a much lower prevalence of month-end clustering among the group that had a more negative perception of receiving these office actions (solid line represents negpercep = 1; Figure S2A). This is consistent with the respondents being aware of the costs of rushing a filing at month-end, and avoiding it if they believe the costs are high.

Finally, we put this all together in regressions of a month-end dummy on costlymiss, negpercep, billcluster (defined as one if they mentioned billing cycles as a possible reason), and clientcluster (defined as one if they mentioned client-imposed deadlines as a possible reason) with month and application year fixed effects. Table S2G presents the results. In line with the corresponding figure, the coefficients on costlymiss are strongly positive and statistically significant throughout. This supports an association between the disincentives related to missing deadlines and month-end clustering. The coefficients on negpercep are negative and generally statistically significant, indicating that attorneys avoid rushing at month-ends if they believe the costs of rushing are high. Billcluster is generally positive, consistent with our argument (though the significance weakens on longer windows), while clientcluster stays insignificant throughout, suggesting that incentives of attorneys may be a relatively more important driver of month-end clustering of filings.
Additional empirical tests on firm routines. In the baseline analysis in Section 4.1, we found that filings by individuals show little or no clustering at month-ends (except before October 1, when the USPTO usually makes fee changes). In line with this, we do not see any month-end effects on quality or complexity for patent filings by individuals (Tables B3 and B4). We also compared large (more than 100 patents over the data period) and small firms (only one patent over the data period), and find that large firms exhibit significantly greater clustering compared with small firms (Table B5). The large firm size effect was robust to the inclusion of lawyer fixed effects and lawyer volume (Table B6). Together, these results strongly establish that larger firms are more likely to have month-end clustering patterns than individuals or small firms.

In addition, following Oyer (1998), we exploit changes in fiscal year-ends to see if clustering patterns within firms shift in the expected direction. Though this focuses not on month-end clustering but on year-end clustering, it provides a useful link between a known routine-related deadline and clustering of filings. We find that, across firms, clustering is indeed correlated with fiscal year-ends; specifically, the share of filings that occur in the last month of the fiscal year is significantly larger than that for any other month (Table B7A). Further, we regressed a dummy variable that is one if the patent was applied in the month in which the old fiscal year ended, on a dummy variable for the time period prior to the fiscal year switch and other controls (application year, month, and firm fixed effects). The coefficient on the old fiscal-year dummy is strongly positive, implying that the propensity to file at the old fiscal year-end diminishes after the switch (by 3.6%, Table B7B). Together, these tests strongly support a role for large firm routines in driving the observed clustering patterns in patent filings.

6.2 Are Inventors the Primary Source of Clustering?

Thus far, our arguments have focused on the final stages of the filing process, just before the application is filed. However, it is possible that routines associated with upstream stages, such as inventors’ performance evaluation cycles, are causing the clustering patterns. Based on our surveys, for several reasons, we believe that the observed clustering is unlikely to be due to inventor behavior.

Our inventor survey suggests that it typically takes anywhere from a week to 12 months (with a mode of 1–3 months) between management approval and patent filing, implying that inventors do not have control over the exact timing of the filing (Table S1A). Our surveys of attorneys yielded a similar timeline between invention disclosure to the attorney and filing (Table S2B). Further, our survey of attorneys confirmed that the exact timing of patent filing is primarily determined by either the law firm attorneys (42% of the responses) or corporate legal staff (43%); only 4% replied that inventors play any role in deciding the filing of the timing (Table S2A).

The modest (if any) role of inventors is consistent with our inventor survey evidence that the number of patents applied for is only one of the criteria for performance evaluation of the R&D organization, and in fact is not even the most frequent one (Table S1B, Panel A). Even for individual R&D staff, though patent filing and grants were somewhat important, it was not the most important criteria for internal performance reviews (Table S1C). As a direct test, we checked for clustering patterns in the reported month of inventor

\[27\] Corresponding changes in complexity and quality were noisy, though generally in the expected direction, suggesting that the magnitude of these effects don’t vary sharply across month- and fiscal-end deadlines (Table B8).
performance evaluation; we did not find evidence for any significant clustering. In fact, fewer patents are filed in the month inventors reported they are evaluated for performance compared with other months (Table S1D). Moreover, no inventor reported having monthly performance evaluations (Table S1F). Deadlines related to inventor performance evaluation were not mentioned as a possible reason for the observed clustering in any of the over 20 interviews we conducted with attorneys. In fact, in these interviews, none of the R&D staff were aware of the clustering pattern in patent filings. Together, these pieces of evidence strongly suggest incentives and penalties related to inventors are unlikely to play a significant role in the observed clustering of patent filings.

6.3 Is the Month-End Clustering due to Economizing on Common Costs?

Firms may choose to file patents together to economize common costs of filing or other coordination reasons unrelated to deadlines (e.g., R&D managers may choose to interact with external attorneys about filings on a certain set of days to avoid distractions to their primary jobs). Alternatively, firms may choose to file all patents related to the same invention on the same day in order to avoid having different priority dates for those patents. At the outset, note that these possibilities imply clustering, but not necessarily at month-ends. Nonetheless, we tried estimating the magnitude, if any, of the bunching of applications due to such reasons. For all applications filed by a firm in a given application-year-month cell, we computed the share of applications filed on any given day. We then computed the deviation of these shares (excess rate) from a hypothetical uniform share based on the number of applications in a given month (e.g., if the firm filed 10 patents in a given month uniformly (i.e., one-a-day), then the uniform daily share will be 1/10; on the other hand, if it filed all the patents on a single date, the average daily share will 1). The mean excess rate in the sample was 0.0336, implying that the probability that applications are processed in a batch is about 3.36 percentage points higher than the expected uniform rate. The excess rate decreased sharply with the number of monthly applications (since the applications are more likely to spread out over the month) but never reached zero, indicating the existence of some bunching during the month, possibly due to economization of costs related to filing. However, this excess rate was significantly higher at month-ends (Table B9). If the clustering is purely due to economization of costs and unrelated to deadlines, there is no reason to expect this excess bunching to be higher at month-ends.

In a different test, we used shared backward citations as an indicator of different patents belonging to the same invention. We constructed all patent-to-patent pairs filed in the same month by the same firm, and computed for each of these approximately 88 million patent pairs, a dummy for sharing a backward citation, and the number of backward citations shared between them. A pair of patents filed by the same firm on the same day is about 12 times more likely to share a backward citation than a pair of patents filed by the same assignee on different days of the same month (0.092 vs. 0.0075). But, we find that conditioning on the pair of patents being filed on the same day, the probability that any two patents share at least one backward citation is significantly lower at month-ends than at non-month-ends (Table B10). Likewise, the number of shared backward citations at month-ends is also significantly lower than that at non-month-ends. This is inconsistent with month-end clustering primarily being driven by the incentive to economize on costs related to the same invention; if that were the case, we should see that for the patent pairs filed on the same

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28We thank an anonymous reviewer for suggesting this test.
day, the pairs filed at month-ends share a greater number of backward citations than that of those filed at non-month-ends.

Is clustering caused by “waiting” to save on common costs? Our theoretical framework posits clustering as arising from rushing to avoid deadline penalties. A plausible alternative is that observed clustering is instead caused by waiting to save on common costs by filing at periodic (incidentally at month-end) checkpoints. A number of results suggest this is not the case. If waiting were causing clustering, one would expect the decline in the rate of filing to be toward the middle or latter part of the month, when the waiting would be for a few days, rather than at the beginning of the month, when the wait would be close to a month. However, the results show a decline in the filing rate at the beginning of the month (e.g., the negative coefficient on days 1–7 in columns 7–9 of Table 1). Further, we observe clustering at the month-end even for subsamples of firms with just one filing per month, which additionally rules out a role for fixed costs savings. Also, there appears to be no plausible reason for higher error rates (or more-complex applications) at month-ends, if clustering were due to waiting; in fact, delayed filing may allow for some errors to be corrected, so that we could expect fewer errors at month-end. Another piece of evidence against this “waiting” hypothesis comes from our analysis of accelerated filing using foreign priority dates (discussed in Section 6.4 below). That analysis shows that applications for which the expiration date to file based on foreign priority falls within the first few days of a month are significantly more likely to be filed in the last five days of the previous month. Because these applications have guaranteed priority dates based on their foreign applications, they have no compelling reason to be accelerated. Nonetheless, the filers of these applications chose to file earlier rather than waiting until the deadline. Hence, this analysis renders additional support for acceleration, rather than waiting, as the driver of clustering patterns we document in this study.

6.4 Is Clustering Driven Solely by Priority Date Considerations?

One of the sources for deadlines discussed in our theoretical framework (Section 2, and Figure 1) is incongruence between the principal and the agent in perceived benefits from an earlier priority date. The heterogeneity of results with technology cycle time (Hypothesis 4, and Section 4.4) confirms a role for priority date considerations. A question that arises is whether all of the observed clustering may be driven by this concern, with no role for any of the other sources for deadlines discussed in our theory (planning, coordination, or working capital considerations). Note that as with economizing on fixed costs, simply rushing for getting an earlier priority date neither directly causes clustering (if all applications get accelerated) nor explains why clustering happens exactly at month-ends.

To check if earlier priority date is the sole consideration, we examined U.S. patent applications that claim priority to a foreign patent. Because these applications already have a priority date, they do not have any rushing benefits related to priority date considerations. However, they do have a statutory deadline to meet; they must be filed within twelve months from the day the foreign application is filed. In fact, we find that these filings also show month-end clustering, though not quite as sharp as other filings (Figure B1 and Table B11). Because such clustering may be driven by the timing of the original filings, we examine if such filings with a statutory deadline on the first few days of a month are more likely to be filed 1–5 days earlier (so that they are filed at the previous month-end). We find evidence of such acceleration, which strongly suggests that there is rushing of tasks to meet a month-end deadline, over and above the benefits of an earlier priority
date (Table B12). Finally, we checked and found that the month-end results for higher complexity and lower work quality generally hold for patents with foreign priority dates (Table B11). These results confirm that early priority dates are not the sole driver of month-end clustering patterns in the data.

6.5 The Role of Special Applications (Provisionals and Continuing Patents)

In our analysis so far, we used data on all applications. However, some of these applications are different from the standard non-provisional application, and there may be a concern that these applications are somehow biasing or driving the results. Our results in this section strongly rule that possibility out. There are four main categories of special applications: (i) provisional, (ii) continuation, (iii) divisional, and (iv) continuation-in-part (explained in detail in the Online Appendix).

First, we checked and verified that the significant month-end clustering, higher month-end complexity and lower month-end work quality (except for the examiner-added cites measure) results hold in the sample excluding these patents, with little change in the magnitude of effects (Table B13).

Second, we examined if clustering patterns for these types conform to what we would expect given the key sources of deadline pressure. Note that in our framework, deadline effects are more likely if applications are: (i) time/effort-intensive (hence, higher fee, which then is likely to generate implications for planning/coordination or working capital), and/or (ii) priority-relevant (so that firms may need task completion using a deadline earlier than the attorney would otherwise want to). Continuation applications are modifications of previously filed patents, and the application cannot contain “new matter” (USPTO MPEP, Section 201.06). Divisional applications are “for a distinct or independent invention, carved out of a pending application and disclosing and claiming only subject matter disclosed in the earlier or parent application” and “often filed as a result of a restriction requirement made by the examiner” (USPTO MPEP, Section 201.06). Thus, the time and effort intensity is limited for both (as confirmed by two practitioners; see “Patent Application Process and Glossary” in the Online Appendix). Further, both these types of applications take the priority date from the original or parent patent application, so the timing of filing of neither type of applications is priority-relevant. Thus, these two types of patents are likely to face little, if any, deadline pressure.

Provisional applications are much shorter than standard non-provisional applications (minimally one cover page plus one or more pages; Quinn 2013), so deadline pressure from time/effort-intensity is likely to be low. But these are relevant for setting priority date – in fact, these are primarily used to secure a priority. In contrast, continuation-in-part applications take priority date from the parent application (USPTO MPEP, Section 201.08), so they have low priority-relevance but can include new matter. Hence they are likely to be more time-intensive than simple continuation applications (also confirmed by two practitioners). Thus, both provisional and continuation-in-part applications are likely to face moderate amounts of deadline pressure. In line with our expectations, we do find a moderate amount of clustering for both provisional and continuation-in-part applications, but little clustering for continuation and divisional applications (Table B14A and B14B).
6.6 Other Robustness Checks

We performed a series of other checks to verify the robustness of our results. We describe them briefly here, referring the reader to the Online Appendix Tables for the detailed results.31

(i) We excluded the ten largest firms in terms of patent volume, and confirmed that our results were not being driven by a handful of outliers (Table B15). (ii) Using an earlier cohort (patents applied before 1995) shows similar results to the baseline, though many of the work quality measures were not available for that period (Table B16). Figure B2 graphically confirms the complexity-related results for that cohort of patents. (iii) We replicated baseline results separately for each of six NBER technology categories (Chemicals, Computers & Communications, Drugs & Medical, Electrical & Electronics, Mechanical, and Miscellaneous). We confirmed that the month-end clustering pattern is stark for all the categories (Table B17A).32 Sorting and work quality results are largely robust as well (Panels A to F of Table B17B). These results confirm that the baseline results are quite broad-based and not influenced by one particular technology. (v) Excluding provisionals, continuations, continuations-in-part, divisionals, and patents with foreign priority more than doubled the magnitude of the observed clustering and work quality effects, particularly on work process (Table B19). (vi) The results were largely robust to using alternative time windows to measure citations and renewal probabilities (Table B20A), and to excluding self-citations (Table B20B). (vii) Using all available data (instead of 2001–04) to analyze examiner citations yielded stronger results (Table B21). (viii) Using a dummy for “application resulting in continuation-in-part” as an alternative measure of complexity (as a sign of the firm continuing to work on that invention), and a dummy for “resulting in divisional” as an alternative measure of work quality (since this action is usually the result of a restriction requirement) revealed that these were more likely to occur for applications filed at month-ends (Table B22). (ix) Including the daily volume of filings (for each firm) as an additional control did not change the substance of the results (Table B23). (x) Using alternative measures of size (assets, sales, and employment) did not affect the results relating to the firm size–clustering association. When jointly included with patent volume (our measure of firm size), only patent volume remained significant (Table B24). (xi) The firm size–deadline clustering association is robust to using application data (Table B25A), and the inclusion of technology class or inventor fixed effects (Table B25B). (xii) We verified robustness of the quality results to splitting the sample by more and less than 20 claims (Tables B26A–B). Interacting the month-end dummy with a dummy for more than 20 claims showed positive interaction terms, though they were generally insignificant (Tables B26C). (xiii) The quality results were robust to including joint firm–claims fixed effects (Table B27A). (xiv) The complexity and quality results were robust to including joint firm–monthly volume for the firm fixed effects, and to using firm–year–month fixed effects instead of firm fixed effects (Table B28).

The coefficient on the provisional dummy in Table B14A is strongly negative for two of the three month-end dummies, and only weakly positive for D1; so, they are not used disproportionately at month-ends. As explained in the Online Appendix, a provisional application is not a panacea to meet deadlines. In general, our interviewees were hesitant to recommend provisionals as a substitute to a fully prepared non-provisional application except in certain strategic cases where the provisional is actually a fully prepared application (e.g., in pharma where a provisional gives the assignee an additional year of protection). The biggest risk to provisionals, they stated, is the inability to add “new matter” to the subsequent non-provisional application without losing the priority date (consistent with the discussion in Quinn 2013).31 We thank anonymous reviewers and the Associate Editor for suggesting some of these robustness checks. 32 Clustering is stronger for Computers & Communications, and Electrical and Electronics (presumably because of stronger competition in these categories), and somewhat lower in Drugs & Medical, relative to the baseline “Miscellaneous category.”
Discussion and Conclusion

Deadlines are ubiquitous, and a particularly critical tool for managers to optimize time allocation of valuable human capital among tasks. Not surprisingly, deadlines have been shown to have real effects, affecting work flows in many contexts (e.g., Carpenter et al., 2012, Asch, 1990). What has remained ambiguous is how the time pressure related to deadlines influences performance quality (e.g., Cadena et al., 2011, Karau and Kelly, 1992, Kelly and McGrath, 1985). What has also remained unexamined empirically is how deadlines influence sorting of tasks for completion. Our study offers robust evidence for a substantial decline in work process quality associated with the clustering of work flows around deadlines. We are also the first, to our knowledge, to document strong sorting of more-complex tasks close to deadlines.

We do so by examining filing of patent applications, a context that offers an opportunity to study a single, relatively uniform process across thousands of firms over a long period of time, and allows us to construct numerous measures of task complexity and work quality. We bring to bear three different methods—formal mathematical modeling combined with a calibration exercise, large-scale statistical analysis, and primary data collection and analyses—on our research question. The insights from these methods complement each other and provide a well-rounded picture of the causes and consequences of deadlines in workplaces. The mathematical model allows us to develop precise hypotheses linking deadline-related time pressure, work flows, task sorting and work quality. Conventional statistical analyses help test these hypotheses, providing us a view of the “costs” of deadline-related time pressure. The mathematical model is also realistic enough to allow us to calibrate key parameters to the data. This allows us to show that the “benefits” from accelerating tasks could indeed be substantial (in terms of savings of working capital), which can be contrasted with the costs due to errors from such acceleration to meet the deadline. Underpinning all of this are insights from our several interviews and surveys.

We find economically significant clustering of patent applications at month-ends. The excess filing at month-ends accounts, on average, for nearly a third (31.4%) of all applications filed on the last working day of the month. Several pieces of evidence strongly indicate that this clustering is due to deadlines. To reiterate our findings in Section 6.1, information from surveys of inventors, law firm and corporate attorneys, and detailed interviews with patent attorneys and inventors directly indicate that routine-related deadlines and associated penalties are the most likely cause of the clustering patterns. Several tests (based on these surveys), using information about frequency of deadlines, concerns about penalties for missing deadlines, and concerns about quality, confirm that clustering patterns are correlated with indicated deadlines, stronger for firms where missing deadlines are perceived badly, and lower where attorneys express concerns about quality perceptions. Several other tests reinforce a strong role for corporate deadlines. Applications by individual assignees, in strong contrast to corporate assignees, generally do not show sharp spikes near month-ends. The propensity to file during month-ends is significantly higher among firms with higher patent volume. Changes in fiscal year-ends are systematically correlated with changes in the clustering patterns of patent filings. We also verified that month-end clustering is unlikely to be driven by the work behavior of inventors, by the incentive to economize on costs by bunching tasks, solely for the seeking of earlier priority dates, or due to the use of non-standard applications such as continuing and provisional applications. Lastly, the results on effect-heterogeneity (Table 4) also provide strong support for the role of deadlines.
Consistent with our hypothesis, we find that clustering of work flows is not driven by marginal applications; rather, applications filed near month-ends are of higher complexity. Based on Table 3, applications filed near month-ends have more claims (0.8–1.7%), contain more drawings (0.3–1.1%), and use more drawing sheets (0.4–1.4%). Conditional on approval, the five-year citation count for patents filed near month-ends is also higher (0.4–1.5%), as is the probability of renewal (0.2–0.3%). These estimates are differences in averages. The effects are substantially higher when we compare rushed filings with those that are not rushed. For instance, the coefficient on claims can be interpreted as a 4.5–6.2% difference between the number of claims in applications influenced by the month-end deadline and other applications. Similarly, patents influenced by the month-end deadlines have 3.8–5.6% more citations, and are 1.0–2.1% more likely to be renewed than other patents. This finding is particularly relevant because, in many modern organizations, workers and work groups often simultaneously undertake multiple tasks of varying complexity, and managers are required to synchronize/coordinate across different tasks and groups. This finding as well as the calibration results suggest that deadlines could have a bigger impact on completion times of more-complex tasks that involve longer time frames.

Turning to the managerial implications of our study, our findings strongly suggest that deadlines can be costly. We find that work quality is indeed significantly lower around month-ends, both unconditionally and conditional on complexity of the application. The effect is stronger for measures that likely reflect errors in the last stage of the filing process. For instance, based on Table 3, applications filed closer to month-ends are about 3.0–4.5% more likely to be considered incomplete by the patent examiners. In relative terms, applications rushed to meet the month-end deadline are 15.5–24.7% more likely to receive such a notice than those that are not. This negative effect on work quality is consistently evident across different measures of short-term consequences, with varying magnitudes of effect. Furthermore, our results suggest deadlines may affect process–related costs and outcome–related costs differently. The impact on longer-term work-outcome measures is smaller; applications filed on month-ends have a 0.25–0.41% lower share of examiner added cites, tend to be approved 0.14–0.46% less often than those filed during other days, and take 1.0–2.4% longer to review. These correspond to a difference of 0.5–3.7% lower rate of approval and 7.7–8.3% longer review time (or about 60 days) between filings rushed to meet the month-end deadline and other filings. The lower magnitudes for longer-term measures suggest that firms are able to fix larger work quality issues reflected in the work-process measures in such a way as to contain longer-term fallout. Being able to obtain such a nuanced view of the costs of deadlines is certainly an advantage of our context.

A rough estimation exercise suggests that the monetary cost of the work process errors from rushed filing can be sizable (Appendix Table A1). The estimated extra cost due to rushed filing is between $614 and $782 per rushed patent, or about 7–8% of the initial filing cost. This estimate is likely to be conservative, as it only considers the direct cost of filing errors, ignoring other, potentially bigger costs due to longer review duration and a lower approval probability due to such errors. Thus, this exercise suggests that the

33\((9.434/1000 + 0.207)/0.207)-1=4.5\%.

34We asked one of the attorneys for the estimated number of hours and associated additional filing fees that are required for dealing with each transaction we use as a measure of work process quality. We then regressed the total cost of such errors on the month-end dummies with all other control variables, and used the coefficient estimate from this regression to calculate the estimated extra cost, conditional on an application being rushed.
productivity loss associated with deadline-related time pressure is not trivial.

In the context of the inverted-U relation between work quality and time pressure posited in the literature (e.g., Bluedorn and Denhardt, 1988), our results suggest that agents in our setting are not likely operating in a zone of “too low” time pressure, where increasing time pressure through deadlines would improve work quality. Rather, they are more likely to be in a zone of “too high” time pressure, where increasing time pressure reduces work quality. This is likely, in part, due to the nature of our data, which pertain to real firms in moderate to intensely competitive sectors rather than to students in a college or in a controlled experiment. In our context, the pressure to innovate is likely to be high enough that firms are already using their human capital close to capacity. We speculate that this is likely to be the case for a significant majority of firms in the private sector, where entry is largely unregulated—that Carpenter et al. (2012) find strikingly large work quality effects when examining deadlines at a government agency is not entirely inconsistent with this conjecture. Thus, our theoretical framework and empirical results are likely to apply more broadly than just within the narrow context of patent filings.

Although the preceding discussion focuses on the costs of deadlines, we do not intend to suggest that deadlines are unambiguously bad. Indeed, our theoretical framework, formal model, and the calibration exercise all specifically incorporate potential gains from deadlines. In our theoretical framework and model, firms impose deadlines because they perceive some benefits from doing so. In line with this, we find larger deadline-related effects for larger firms (for whom the benefits are likely to outweigh the fixed costs of deadline monitoring) and in sectors with faster technological changes (where the principal is likely to perceive stronger benefits from obtaining an earlier priority date than the agent). Further, imposing deadlines increases the quantity of output by accelerating task completion. Our calibration exercise suggests, within the bounds of its assumptions, that this acceleration is likely to be small (about two days or 1.8%) in our context. On the other hand, from the patent attorney’s standpoint, deadlines may be more beneficial; our exercise suggests that working capital savings from billing earlier can be relatively large (around 30% reduction in days of unbilled balances).

In conclusion, our study reiterates the need to carefully evaluate the gains from reduced task duration against costs from poorer work quality when designing and implementing routines with deadlines. One way to understand the trade-offs and arrive at an optimal design would be to experiment with alternative deadline periods and the strength of incentives. We attempted something along these lines in our calibration exercise, and find that increasing billing frequency while reducing deadline penalties could reduce error rates while moderating working capital pressures. This suggests that separating patent-related deadlines from other organizational deadlines such as accounting, billing, or reporting deadlines may be beneficial to patenting outcomes. In our context, reexamining contractual arrangements with law firms (e.g., pay-per-filing vs. hourly billing), along with the routine-generated deadlines may also be useful. Finally, survey evidence suggests that lawyers who perceive negative consequences from sloppy work tend to cluster work less. So, managers could consider tracking such work process measures and using these as part of key performance indicators for agents to improve outcomes.
References


[38] Sampat, B. N. 2012, Examiner Citation Data, http://hdl.handle.net/1902.1/18735, Harvard Dataverse, V.2.

APPENDIX

MODEL. We present a model of deadline-driven behavior that ties the clustering, complexity differential and higher error rates observed around month-ends. Agents complete independent tasks, possibly of varying complexities, that arrive randomly over time. The optimal time taken to complete a given task depends on the costs and benefits to the agent from completing that task. Deadlines are periodically occurring “checkpoints”, when a principal imposes a cost on the agent for having incomplete tasks.

Tasks and Task Arrival Process. Tasks vary on complexity, a continuous scalar \( x \in [1, X] \), with strictly positive support over the domain. Net benefits excluding error costs to completing a task are \( \frac{a(x)}{t} \), with \( a(x) \) positive, bounded, and continuous, and \( a'(x) > 0 \). The error function (normalized in cost units) is: \( E(x, t) = \frac{b(x)}{2} \left( \frac{1}{t} \right)^2 \), where \( x \) is complexity of the task, \( t \) is the duration, and \( b(x) \) is a positive, bounded, and continuous function. We assume \( b'(x) > 0 \).

Task arrival is poisson with arrival rate \( \lambda \), with the number of arrivals per instant distributed uniformly and i.i.d over \( \{0,1,2,\ldots,M\} \). Each task has a complexity drawn from a distribution that is uncorrelated with the time of arrival, so that both number and complexity of applications are i.i.d over time. Hence, for a task with complexity \( x \), optimal task duration \( t^* \) is \( t^* = \frac{b(x)}{a(x)} \). We assume that \( a(x) \) and \( b(x) \) are such that \( \frac{b(x)}{a(x)} \) is strictly increasing in \( x \), and \( \frac{b(1)}{a(1)} > 0 \), so that more-complex tasks have a longer optimal duration, and the duration for the least complex task is non-zero.

Proposition 1: If \( t^*_a(x) < t^*_b(x) \) \( \forall x \), then it is optimal for principals with task volume \( \frac{M}{2} \lambda \) above a cutoff \( V \) to set a non-zero deadline penalty, i.e., \( \gamma > 0 \). (Hypothesis 4)

Proof. Imposing a small \( \gamma = \epsilon > 0 \) cost on the agent will lead them to accelerate some tasks, which improves the principal’s payoff. At very low volumes, savings from acceleration do not cover the monitoring cost \( F_D \).

Deadline penalties. Assume that a task of duration \( t^* \) arriving at instant \( d \) is completed at instant \( d + t^* \). Let \( z \) be the time between the planned end time and the closest prior period-end deadline. Then \( z = \text{Mod}(d + t^*, D) \), if \( t^* > (D - d) \) where \( d \) is the instant that the task arrives. Then, it follows that:

Lemma 1: For any given \( t^* \), \( z \) will be distributed uniformly over the set \([0, t^*]\).

Forward-looking, rational agents will accelerate a task of complexity \( x \) to be finished by prior period-end if
\[
\frac{a(x)}{t^*} - \frac{b(x)}{2} \left( \frac{1}{t^* - z} \right)^2 > \frac{a(x)}{t} - \frac{b(x)}{2t^2} - \gamma c(x).
\]
That is, iff
\[
f(t^*) \left[ \frac{z^2}{2(t^* - z)^2} \right] < \gamma.
\]

Work Flows. Lemma 2: For any given \( t^* \) and \( \gamma \), we can find a \( z \) close enough to zero that \( f(t^*) \left[ \frac{z^2}{2(t^* - z)^2} \right] < \gamma \) holds.

Proof. The numerator \( z^2 \) can be made arbitrarily close to zero while keeping the denominator bounded below at a positive value.

Lemma 3: For any given \( t^* \) and \( \gamma \), there is an upper bound, \( z^* (t^*, \gamma) \) above which it is not optimal to accelerate so as to finish the task by the deadline. The upper bound has the following properties: (i) \( z^* = t^* \left( \frac{\mu}{1 + t^* \mu} \right) \) where \( \mu = \sqrt{\frac{2\gamma}{f(t^*)}} \); (ii) \( z^* \) is increasing in \( \gamma \) for any given \( t^* \); (iii) \( \frac{z^*}{t^*} \) is increasing in \( \gamma \) for any given \( t^* \); and (iv) If \( f(t^*) \) is non-increasing in \( t^* \), then \( z^* \) is increasing in \( t^* \) for any given \( \gamma \).
\( \gamma \) and \( \text{sgn} \left[ \frac{\partial^2(z^*/t^*)}{\partial t^* \partial \gamma} \right] = - \text{sgn} \left[ \frac{\partial(z^*/t^*)}{\partial t^*} \right] \) for high enough \( \gamma \).

Proof. See Online Appendix for proof.

From now on, we assume \( T > D \) and \( \gamma < T \) where \( \bar{\gamma} \) is the smallest \( \gamma \) such that \( z^*(T, \bar{\gamma}) = D \). Then, tasks are only accelerated to the closest deadline.

Proposition 2: In a regime with a deadline penalty, there is clustering of task completions at the period-end. The additional mass of tasks completed at the deadline is

\[
\int_{\gamma}^{T} E(x) dt.
\]

(Hypothesis 1)

Corollary 1: The clustering of task completions is increasing in \( \gamma \).

Proof. Follows from Lemmas 2 and 3, and \( z \) being distributed uniformly for any given \( t^* \). Corollary follows directly from point (iii) in Lemma 3.

Task Sorting. The slope of \( f(t^*) \) determines if the fraction of tasks to be accelerated (as determined by \( \frac{z^*}{T} \)) is increasing or decreasing in complexity.

Proposition 3: If \( f'(t^*) < \frac{2f(t^*)}{t^*} \) for all \( t^* \), then average complexity is higher for tasks accelerated to the deadline. (Hypothesis 2)

Corollary 2: If \( f(t^*) \) is non-increasing in \( t^* \), then average complexity is higher for accelerated tasks.

Proof. When the derivative of \( f(t^*) \) is small enough, a greater fraction (\( \frac{z^*}{T} \)) of more-complex applications get accelerated. So, the mean complexity among accelerated tasks is more than the population average. The corollary follows immediately as a special case of the proposition. See Online Appendix for details.

Work Quality

Proposition 4: In a deadline-penalty regime with a low enough \( \gamma \) such that for any given complexity, there is some fraction of tasks that are unaccelerated, if \( f'(t^*) < \frac{2f(t^*)}{t^*} \), unconditional on complexity, there is a higher expected error rate for tasks completed at the deadline. (Hypothesis 3a)

Proof. At optimal duration, error rate is \( E(x) = \frac{\text{cost units}}{2\text{cost units}} \), i.e., it is increasing in complexity. With deadlines, more-complex tasks are accelerated. So, the average error rate is higher for tasks completed at period-end.

Proposition 4b: With a deadline penalty, conditional on complexity, there is a higher expected error rate for tasks completed at the deadline. For every complexity, error increases as \( \gamma \) increases. (Hypothesis 3b)

Proof. For a given \( t^* \) and \( z \), the additional error due to acceleration is \( \frac{b(x)}{2(t^* - z)T} - \frac{b(x)}{2T} > 0 \). So, conditional on complexity, error rates are higher for \( \gamma > 0 \). Since \( z^* \) is increasing in \( \gamma \), error rate is increasing in \( \gamma \).

---

36Our assumptions about \( a(x) \) and \( b(x) \) imply that: (a) the optimal task duration is higher for more-complex tasks, (b) the maximized net benefits are higher for more-complex tasks, and (c) there is a one-to-one correspondence between \( x \) and \( t^* \). Thus, complexity is a task characteristic that makes it optimal to spend longer time to execute. While we characterize tasks using a scalar, \( x \), it could reflect two characteristics — conceptual complexity (which makes the application difficult to draft) and economic importance (which makes the application more valuable). \( x \) directly reflects conceptual complexity since increasing conceptual complexity makes the optimal time frame longer. With regard to economic importance, the benefit of filing early (\( a(x) \)) is likely increasing in importance, which is consistent with our assumption that \( a'(x) > 0 \). But whether optimal duration would increase in importance would depend on how error costs increase with importance. Since the error function is in cost units, \( b(x) \) could indeed be higher for more important patents, as the economic consequence of errors increases in severity with importance. Then, if \( b(x) > a(x) \) where \( x \) is importance, \( t^*(x) \) will be increasing in importance. To summarize, it is plausible to interpret complexity \( x \) as “weightiness” of the task, where weightiness arises from either conceptual complexity (measured as larger number of claims, more drawings or more-complex drawings), or from importance (measured as number of forward cites or renewal probability) if increasing importance, ceteris paribus, increases the optimal duration for task completion.
<table>
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<th>D1</th>
<th>D2</th>
<th>D3</th>
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<td>614.04**</td>
<td>782.02**</td>
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<td></td>
<td>(182.82)</td>
<td>(187.64)</td>
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<td>Percentage of initial filing cost</td>
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<td>(2.01)</td>
<td>(2.06)</td>
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</table>

The top row presents the additional per-patent cost to correct errors, conditioning on the filing being rushed. “Total cost” is regressed on a month-end dummy, with log firm-year size, application year, month and firm fixed effects as controls. “Total cost” is the cost to address the eight actions (used to measure work process quality) based on the number of these actions, the current USPTO fee schedule, and estimates of attorney effort (at US$250/hr) obtained from a practicing attorney. Initial filing cost is taken as $8,100 = 30 hrs * $250/hr + $1,600. N=92,533. Std. errors clustered by firm; +p :< 0.1, * : p < 0.05, ** : p < 0.01.

Figure 1: Model Framework – Causes and Consequences of Deadlines
Figure 2: Patent Filings Day Share of Year Total

Graph presents day-share of filings for corporate assignees.

Corporate Assignees

Graph presents day-share of filings for individual assignees.

Individual Assignees

Graph presents difference between day-share of filings for corporate and individual assignees.

Corp. – Indiv.
Figure 3: Month-ends, Application Complexity, and Application Quality

In each of the figures, the line denotes predicted fractional polynomial fit; the area denotes 95% confidence interval; the horizontal axis indicates working day of the month. The dependent variable, from the first figure to the last in the top row, is log number of claims in the application, log number of citations to the patent within five years of application, and a dummy variable equal to 1 if fees for renewal of patent was paid 3.5 years after grant of the patent and 0 otherwise, respectively. The dependent variable, from the first figure to the last in the bottom row, is a dummy variable equal to 1 if the application received an “Application Incomplete” notice from the USPTO and 0 otherwise, a dummy variable that is 1 if the application was approved by November 2011 and 0 otherwise, and log number of days between application date and grant date for successful patent applications, respectively. All dependent variables are de-meaned of firm fixed effects.
## Table 1: Work Flow Clustering Around Month-ends

<table>
<thead>
<tr>
<th></th>
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<td>3</td>
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<td>-0.214*</td>
<td>-0.053</td>
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<tr>
<td></td>
<td>(0.091)</td>
<td>(0.097)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>Days 8-15</td>
<td>-0.283**</td>
<td>-0.122</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.080)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Days 16-23</td>
<td>0.0133+</td>
<td>0.028</td>
<td>0.190</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.083)</td>
<td>(0.116)</td>
</tr>
<tr>
<td>D1</td>
<td>0.553+</td>
<td>0.164</td>
<td>0.389**</td>
</tr>
<tr>
<td></td>
<td>(0.320)</td>
<td>(0.246)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>D3</td>
<td></td>
<td>0.587**</td>
<td>0.234*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.140)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>D5</td>
<td></td>
<td>0.595**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.135)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Dn-Days 1-7</td>
<td>0.928**</td>
<td>0.802**</td>
<td>0.647**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.138)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>N</td>
<td>366</td>
<td>366</td>
<td>366</td>
</tr>
<tr>
<td>Dn-Days 1-7 (excl. September)</td>
<td>0.753*</td>
<td>0.688**</td>
<td>0.554**</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(0.137)</td>
<td>(0.106)</td>
</tr>
</tbody>
</table>

Note: The table presents coefficients from OLS regressions. The dependent variable is the day-share of annual patent applications for firms (columns 1-3), for individual assignees (4-6) and their difference (columns 7-9). The independent variables are dummy variables corresponding to the period mentioned in the rows. These regressions use data on granted patents from 1976 to 2009. The day-share for a given day is computed as the ratio of the number of successful patents applied on that day to the total number of successful patents over the sample period. The last row reestimates the same regressions, excluding the month of September (October 1 is the date when USPTO fees increase). **: p<0.01, *: p<0.05, +: p<0.1. Robust standard errors in parentheses. Coefficients and standard errors multiplied by 1,000.
Table 2: Task-Sorting (Complexity) at Month-ends

<table>
<thead>
<tr>
<th>Measure</th>
<th>D1</th>
<th>D3</th>
<th>D5</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log number of claims</td>
<td>17.354**</td>
<td>9.434*</td>
<td>7.953*</td>
<td>1,801,602</td>
</tr>
<tr>
<td></td>
<td>(3.156)</td>
<td>(2.259)</td>
<td>(2.155)</td>
<td></td>
</tr>
<tr>
<td>Log number of drawings</td>
<td>11.170**</td>
<td>5.165*</td>
<td>2.864+</td>
<td>2,829,361</td>
</tr>
<tr>
<td></td>
<td>(3.274)</td>
<td>(2.070)</td>
<td>(1.729)</td>
<td></td>
</tr>
<tr>
<td>Log number of drawing sheets</td>
<td>14.444**</td>
<td>7.444**</td>
<td>4.469**</td>
<td>2,829,361</td>
</tr>
<tr>
<td></td>
<td>(3.091)</td>
<td>(1.910)</td>
<td>(1.594)</td>
<td></td>
</tr>
<tr>
<td>Log number of drawings per drawing sheet</td>
<td>-11.483**</td>
<td>-8.051**</td>
<td>-4.337**</td>
<td>2,829,361</td>
</tr>
<tr>
<td></td>
<td>(2.596)</td>
<td>(1.661)</td>
<td>(1.396)</td>
<td></td>
</tr>
<tr>
<td>Log number of cites (5 years)</td>
<td>15.018*</td>
<td>6.116*</td>
<td>3.897+</td>
<td>2,633,488</td>
</tr>
<tr>
<td></td>
<td>(3.018)</td>
<td>(1.968)</td>
<td>(1.682)</td>
<td></td>
</tr>
<tr>
<td>Renewal (3.5 years)</td>
<td>2.823+</td>
<td>2.051+</td>
<td>2.161*</td>
<td>1,938,296</td>
</tr>
<tr>
<td></td>
<td>(1.253)</td>
<td>(0.859)</td>
<td>(0.765)</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table presents regressions of various work complexity measures on a month-end dummy. Log firm-year size, and application year, month, and firm fixed effects are included in all models. All coefficients and standard errors multiplied by 1,000. Claims are based on application data from 2001 to 2009. Drawing and drawing sheets are based on patent data for 1976 to 2009. 5-year citations and 3.5-year renewal are based on patent data from 1976 to 2004 and 1980 to 2005, respectively. Standard errors are clustered by firm. **: p<0.01, *: p<0.05, +: p<0.1.
Table 3: Work Quality around Month-ends

<table>
<thead>
<tr>
<th>Measure</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>D1</td>
<td>D3</td>
<td>D5</td>
<td>D1</td>
<td>D3</td>
<td>D5</td>
<td>N</td>
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<tr>
<td></td>
<td>(s.d.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Work process measures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Application</td>
<td>0.290</td>
<td>45.820**</td>
<td>36.129**</td>
<td>29.983**</td>
<td>45.203**</td>
<td>35.897**</td>
<td>29.773**</td>
<td>92,533</td>
</tr>
<tr>
<td>Incomplete Notice</td>
<td>(0.454)</td>
<td>(10.737)</td>
<td>(7.063)</td>
<td>(5.550)</td>
<td>(10.697)</td>
<td>(7.050)</td>
<td>(5.525)</td>
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</tr>
<tr>
<td>Separate Inventor Oaths</td>
<td>0.262</td>
<td>48.661**</td>
<td>37.288**</td>
<td>32.278**</td>
<td>48.175**</td>
<td>37.105**</td>
<td>32.112**</td>
<td>92,533</td>
</tr>
<tr>
<td>Oaths</td>
<td>(0.440)</td>
<td>(8.605)</td>
<td>(6.208)</td>
<td>(4.871)</td>
<td>(8.578)</td>
<td>(6.194)</td>
<td>(4.866)</td>
<td></td>
</tr>
<tr>
<td>Additional App. Filing Fees</td>
<td>0.314</td>
<td>46.607**</td>
<td>36.410**</td>
<td>30.267**</td>
<td>45.563**</td>
<td>36.220**</td>
<td>30.095**</td>
<td>92,533</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(9.403)</td>
<td>(6.745)</td>
<td>(5.405)</td>
<td>(9.383)</td>
<td>(6.738)</td>
<td>(5.401)</td>
<td></td>
</tr>
<tr>
<td>New/Additional Drawings</td>
<td>0.133</td>
<td>14.600*</td>
<td>15.278**</td>
<td>9.535**</td>
<td>14.376**</td>
<td>15.194**</td>
<td>9.459**</td>
<td>92,533</td>
</tr>
<tr>
<td></td>
<td>(0.340)</td>
<td>(6.109)</td>
<td>(3.960)</td>
<td>(3.520)</td>
<td>(6.109)</td>
<td>(3.955)</td>
<td>(3.505)</td>
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<tr>
<td></td>
<td>(0.491)</td>
<td>(7.820)</td>
<td>(5.502)</td>
<td>(4.845)</td>
<td>(7.810)</td>
<td>(4.846)</td>
<td>(4.859)</td>
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<tr>
<td>Non-Final Rejection</td>
<td>0.834</td>
<td>18.840**</td>
<td>8.239*</td>
<td>5.178</td>
<td>18.347**</td>
<td>8.053*</td>
<td>5.009</td>
<td>92,533</td>
</tr>
<tr>
<td></td>
<td>(0.372)</td>
<td>(5.493)</td>
<td>(4.071)</td>
<td>(3.632)</td>
<td>(5.489)</td>
<td>(4.056)</td>
<td>(3.615)</td>
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<tr>
<td>Request for Extension of Time</td>
<td>0.387</td>
<td>18.515*</td>
<td>7.948</td>
<td>8.980*</td>
<td>17.672**</td>
<td>7.631</td>
<td>8.611+</td>
<td>92,533</td>
</tr>
<tr>
<td></td>
<td>(0.487)</td>
<td>(7.798)</td>
<td>(5.371)</td>
<td>(4.447)</td>
<td>(7.788)</td>
<td>(5.363)</td>
<td>(4.481)</td>
<td></td>
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<tr>
<td>Restriction/Election Requirement</td>
<td>0.149</td>
<td>19.175**</td>
<td>12.913**</td>
<td>16.843**</td>
<td>16.567**</td>
<td>11.933**</td>
<td>15.958**</td>
<td>92,533</td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(5.601)</td>
<td>(4.384)</td>
<td>(3.674)</td>
<td>(5.540)</td>
<td>(4.233)</td>
<td>(3.576)</td>
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<tr>
<td>Quality Factor 1</td>
<td>-0.000</td>
<td>109.180**</td>
<td>83.961**</td>
<td>71.542**</td>
<td>107.791**</td>
<td>83.438**</td>
<td>71.069**</td>
<td>92,533</td>
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<td>(0.945)</td>
<td>(19.413)</td>
<td>(13.826)</td>
<td>(10.93)</td>
<td>(19.336)</td>
<td>(13.793)</td>
<td>(10.882)</td>
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<td><strong>Work outcome measures</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Examiner Add. Cite Share</td>
<td>0.596</td>
<td>0.254</td>
<td>4.140+</td>
<td>4.095*</td>
<td>0.780</td>
<td>4.440*</td>
<td>4.236*</td>
<td>627,209</td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td>(3.388)</td>
<td>(1.980)</td>
<td>(1.788)</td>
<td>(3.383)</td>
<td>(2.005)</td>
<td>(1.805)</td>
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</table>

Unconditional | Conditional on task complexity
<table>
<thead>
<tr>
<th>Measure</th>
<th>(1) Mean (s.d.)</th>
<th>(2) D1</th>
<th>(3) D3</th>
<th>(4) D5</th>
<th>(5) D1</th>
<th>(6) D3</th>
<th>(7) D5</th>
<th>(8) N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Application</td>
<td>0.803 (0.398)</td>
<td>-1.441</td>
<td>-4.578*</td>
<td>-4.456*</td>
<td>-1.626</td>
<td>-4.672**</td>
<td>-4.549**</td>
<td>785,051</td>
</tr>
<tr>
<td>Approved</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Review</td>
<td>6.907 (0.479)</td>
<td>23.139**</td>
<td>14.246**</td>
<td>9.011**</td>
<td>20.369**</td>
<td>12.985**</td>
<td>7.817**</td>
<td>557,383</td>
</tr>
<tr>
<td>Duration</td>
<td></td>
<td>4.015</td>
<td>(2.526)</td>
<td>(2.403)</td>
<td>(3.819)</td>
<td>(2.587)</td>
<td>(2.311)</td>
<td></td>
</tr>
</tbody>
</table>

This table presents coefficients from regressions of a dependent variable (row) on a month-end dummy (D1, D3 or D5). All work process measures are dummy variables defined as 1 if the application had that transaction, and 0 otherwise. Quality Factor 1 is based on factor analysis (PCA with varimax rotation) of the 8 work process based measures. The first factor is the only factor with an eigenvalue greater than 1 (2.23). The next factor has an eigenvalue of 0.53. Examiner added citation share is defined as the number of citations added by the examiner divided by the total number of citations. Application approved is a dummy variable that equals 1 if the application was approved and 0 otherwise. Log review duration is the number of days between application date and grant date for successful patent applications. Throughout, only data from 2001-04 are used. Log firm-year size, application year, month, and firm fixed effects are included in all models. In the models testing conditional on “complexity,” log number of claims is an additional control. **: p<0.01, *: p<0.05, +: p<0.1. Standard errors are clustered by firm. Coefficients and standard errors multiplied by 1,000.
TABLE 4: Firm Size, Speed of Innovation and Deadline Effects

<table>
<thead>
<tr>
<th></th>
<th>Firm Size Interaction</th>
<th>Technology Cycle Time Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D1</td>
<td>D3</td>
</tr>
<tr>
<td>Month-end clustering</td>
<td>2.842**</td>
<td>5.533**</td>
</tr>
<tr>
<td>(0.582)</td>
<td>(0.702)</td>
<td>(0.676)</td>
</tr>
<tr>
<td>Log claims</td>
<td>7.306*</td>
<td>7.678**</td>
</tr>
<tr>
<td>(3.148)</td>
<td>(2.130)</td>
<td>(1.745)</td>
</tr>
<tr>
<td>(1.879)</td>
<td>(1.279)</td>
<td>(0.986)</td>
</tr>
<tr>
<td>Renewal (3.5 yrs.)</td>
<td>0.445</td>
<td>0.575</td>
</tr>
<tr>
<td>(0.625)</td>
<td>(0.395)</td>
<td>(0.326)</td>
</tr>
<tr>
<td>(3.835)</td>
<td>(2.516)</td>
<td>(2.000)</td>
</tr>
<tr>
<td>(3.154)</td>
<td>(2.224)</td>
<td>(1.724)</td>
</tr>
<tr>
<td>Add. Filing Fees</td>
<td>2.886</td>
<td>4.002+</td>
</tr>
<tr>
<td>(3.428)</td>
<td>(2.411)</td>
<td>(1.887)</td>
</tr>
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<td>Exam. Add. Cites</td>
<td>1.511</td>
<td>0.069</td>
</tr>
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<td>(1.857)</td>
<td>(1.165)</td>
<td>(1.012)</td>
</tr>
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<td>App. Approved</td>
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<tr>
<td>(1.882)</td>
<td>(1.045)</td>
<td>(0.811)</td>
</tr>
<tr>
<td>Log review time</td>
<td>3.520</td>
<td>2.722+</td>
</tr>
<tr>
<td>(2.368)</td>
<td>(1.518)</td>
<td>(1.245)</td>
</tr>
</tbody>
</table>

Note: The first row of this table presents the coefficients on log firm-year size (columns 1-4) and on log technology cycle time (columns 5-9) from a regression of a month-end dummy (D1, D3, or D5) on these variables and controls. The subsequent rows replicate the corresponding specifications in Tables 3 and 4 with a firm size-end of month dummy interaction included (columns 1-4) and a log cycle time-end of month dummy interaction (columns 5-8) included. Each of the cells in these rows presents the coefficient estimate and the standard error of the interaction term between firm-year size or log cycle-time, and end-of-month dummy. We use patent data when examining technology cycle time since technology data are not available in the application data. Application year and month fixed effects are included in all models, and grant year fixed effect is included in addition in the log cites and renewal regression. **: p<0.01, *: p<0.05, +: p<0.1. Standard errors are clustered by firm. Coefficients and standard errors multiplied by 1,000.
TABLE 5: Benefits of Deadlines: Results from the Calibration Exercise

<table>
<thead>
<tr>
<th>Model Calibration</th>
<th>Std. Penalty Parameter=1</th>
<th>Std. Penalty Parameter=2</th>
<th>Std. Penalty Parameter=1/2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Share Diff Accel Accel</td>
<td>Share Diff Accel Accel</td>
<td>Share Diff Accel Accel</td>
</tr>
<tr>
<td>Sample Actuals</td>
<td>7.0% 4.1% 1.5 d 7.5 d</td>
<td>31.3% 13.1% 1.8% 31.6%</td>
<td></td>
</tr>
<tr>
<td>Calibrated Model</td>
<td>7.0% 4.2% 1.5 d 7.5 d</td>
<td>34.7% 12.0% 1.8% 31.6%</td>
<td></td>
</tr>
</tbody>
</table>

Standardized Values

| Sample Actuals    | 31.3% 13.1% 1.8% 31.6% |
| Calibrated Model  | 34.7% 12.0% 1.8% 31.6% |

Predicted Counterfactuals Based on Model Calibration (Standardized Values)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekly deadline (5 days)</td>
<td>36.4% 17.6% 1.6% 8.3%</td>
<td>46.9% 20.9% 2.1% 8.3%</td>
<td>25.5% 11.3% 1.3% 7.9%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bi-weekly deadline (11 days)</td>
<td>36.4% 13.1% 1.6% 17.6%</td>
<td>47.3% 15.7% 2.1% 18.0%</td>
<td>26.3% 10.9% 1.3% 16.8%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly deadline (22 days)</td>
<td>34.7% 12.0% 1.8% 31.6%</td>
<td>46.2% 13.8% 2.2% 31.9%</td>
<td>24.4% 6.7% 1.5% 30.9%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi-quarterly (33 days)</td>
<td>34.7% 10.0% 1.7% 41.7%</td>
<td>46.3% 13.5% 2.2% 41.9%</td>
<td>23.2% 1.9% 1.3% 41.2%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarterly deadline (66 days)</td>
<td>33.6% 10.4% 1.6% 60.7%</td>
<td>45.3% 12.5% 2.1% 60.3%</td>
<td>21.2% 2.0% 1.2% 61.7%</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Unstandardized value of period end share refers to the share of monthly filings filed on the last day of the month. Unstandardized value of error difference (duration acceleration) refers to the difference between the average error rate (duration) of applications filed on the last day of the month and those filed on other days. Unstandardized value of unbilled balance acceleration refers to the savings in days of unbilled balances between the applications filed on the last day of the month relative to those filed on other days. Standardized values of period end share refer to the share of the last day filings that are accelerated. Standardized values of error difference (duration acceleration) refer to the difference between the error rate (duration) of rushed applications filed on the last day of the month and those of other applications. Standardized value of unbilled balance acceleration refers to the savings in days of unbilled balances between rushed applications filed on the last day of the month relative to those filed on other days.