Organizational Adaptation, Task Complexity, and Effective Administration of Unemployment Programs in the American States

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ABSTRACT

IT modernization reforms are intended to improve administrative performance by increasing both effectiveness and efficiency in program delivery. Performance benefits are manifested by a reduction in agency-induced administrative errors, while also reducing performance gaps between high and low complexity task caseloads. These claims are evaluated by assessing the impact of IT modernization reforms adopted by state unemployment insurance payment (UIP) agencies from 2002-2022. The statistical evidence reveals that these reforms have discernible, unconditional dynamic effects for lowering overall program error rates, as well as for reducing both absolute and relative Type I program error rates relating to program efficiency. Yet, little support is garnered that IT reforms close the performance gap between high and low task complexity caseloads. On a broader level, this evidence corroborates existing claims that technological-based administration is inherently non-neutral since program efficiency is improved in relation to program social equity in both absolute and relative terms.

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Reducing inefficiency and waste from administration is critical for improving both government performance and accountability. Efficiency in the public sector is a key tenet of many public management reforms (e.g., Hood 1991). One specific set of reforms has been the Improper Payments Elimination and Recover Improvement Act of 2012, which states its purpose as to identify and prevent "*payment error, waste, fraud, and abuse within Federal spending*." (*U.S. Public Law 112-248*) in the administration of U.S. major federal programs. These reforms often require the leveraging of information technology to streamline administrative processes while reducing human errors and bias in decision-making (Compton, et al. 2022; Wenger and Wilkins 2009) and to reduce search costs and coordination costs, ensuring that citizens benefit from public services equitably (Cordella and Tempini 2023; Herd and Moynihan 2019). As government operations become increasingly automated through the integration of artificial intelligence across various government functions (Bullock, et al. 2022), the question of whether such technology-driven reforms enhance administrative performance, and for whom do these improvements occur has become increasingly relevant for understanding effective governance.

This study addresses a pair of issues overlooked regarding how IT-driven reforms can alter administrative performance. First, this study focuses on how administrative performance dynamically adapts to administrative reform. This behavior cannot be observed from static evaluations of performance change comparisons before and after reforms. Adopting new technology is often costly and challenging, necessitating organizations to adjust their practices and sometimes undergo agency-wide restructuring to fully realize performance improvements (e.g., Repenning and Sterman 2002; Schwab 2007; Tyre and Orlikowski 1994). This process requires agencies to engage in significant adjustments to ensure effective adaptation. Second, very few studies provide direct meaningful comparisons between a public agency's efficiency and equity gains benefitting from information technology. This is a critical issue since administrative reforms can exert differential effects on agency performance, whereby some agencies realize gains while other organizations experience setbacks (Krause and Jin 2020). Further, algorithms used in public administration settings focused solely on maximizing accuracy can inadvertently perpetuate or exacerbate existing social inequities involving administrative governance (Patty and Penn 2023).

To bridge this gap, this study aims to understand how IT-driven administrative reforms influence performance based on program error rates when making eligibility determinations. Using aggregated monthly-level program error rates audit data from the U.S. Department of Labor from 2002 through June 2022, we analyze how state agencies adapt to information technology (IT) modernization reforms adopted by 28 states. A nonparametric estimation strategy is employed to estimate organizational adaptation effects that reflect dynamic performance changes attributable to these IT reforms. Because this empirical approach accounts for both variable and nonlinear rates of organizational adaptation through time, it offers a novel, flexible estimation strategy for analyzing the dynamic consequences of technological reforms in shaping administrative performance.

Drawing on organizational theory, combined with insights from the existing research on government information technology, we argue that IT reforms reduce administrative errors through time, and this salutary effect will be more acute as a state UIP agency's task complexity increases. The statistical evidence reveals that while IT reforms yield an unconditional decline in overall program error rates for state UIP agencies, most of these performance benefits are manifested by a dynamic reduction in Type I program errors relating to benefit overpayments. These benefits, however, are generally absent when it comes to improving the performance gap between high and low complexity task caseloads. In short, IT reforms in state UIP agencies have offered tangible efficiency-based improvements in reducing Type I program errors involving benefit overpayments – both in absolute terms, and also relative to Type II program error rates. These latter set of findings are consistent with research emphasizing that technological forms of administrative governance place a greater relative emphasis on efficiency vis-à-vis equity in the administration of government programs (De Boer and Raaphorst 2023; Schiff, et al. 2021).

IMPACT OF IT MODERNIZATION REFORMS ON ADMINISTRATIVE PERFORMANCE

Information technology (IT) assists storage, acquisition, and retrieval of information which leads to enhanced organizational intelligence that can be used to assess programs and to establish procedures to address shifting customer expectations. For this reason, technological dimension of organizational adaptation "*…. supports the ability to assimilate and communicate data to provide ongoing signals about how the organization is adapting to changes in the environment*." (Brown and Brudney 2003: 31). IT seeks to improve administrative performance by streamlining the administrative process. This entails process standardization (e.g., see Bovens and Zouridis 2002), reducing the length of forms (Dunleavy, et al. 2006a: 485), and hence, improves the quality of decision making by reducing human errors associated with manual data entry and paper-based processing (Pang, et al. 2014; Wener and Wilkins 2009).

IT reforms represent a common type of administrative reform undertaken by a wide array of agencies performing different missions (Borins 2014; Choi and Chandler 2020; Wenger and Wilkins 2009). Because IT modernization efforts have major long-term consequences for administrative performance, they represent wholesale changes to administrative workflow, and not merely a system update or modification of existing technology (Bovens and Zouridis 2002; Dunleavy, et al 2006b). The IT modernization reforms analyzed in this study constitute a major change for how state UIP agencies process task caseloads. Although IT modernization is only one such factor that can affect agency performance, it represents a core administrative function common across public agencies.

In the realm of state UIP agencies charged with administering unemployment insurance benefits, IT modernization reforms entail a transition towards the use of "*…..application technology that inherently supports web-based services and object-oriented paradigms in combination with relational database technology.*" (National Association of State Workforce Agencies 2010: 7). These reforms seek to sharply reduce traditional 'paper-based' case processing of unemployment benefits with a greater reliance on web-based services and relational database technology, thereby reducing reliance on manual processes (U.S. Department of Labor Office of Inspector General 2021). IT modernization reforms intend to improve both timelines and accuracy by providing both immediate validation and processing of unemployment claims employing these technologies. Integrated filing systems accelerate claims processing by standardizing the filing process for citizens and the adjudication process for staff. This stands in direct contrast to state UIP agencies lacking IT modernization reforms that rely on using separate platforms for filing, validating, and updating claimant information. Antiquated systems are susceptible to contributing to claimant benefit errors, while increasing (manual) workload (National Association of State Workforce Agencies 2010: 10-11; U.S. Government Accountability Office 2021: 22). Empirical evidence reveals that the introduction of federal-state integrated database of employment records – i.e., National Database of New Hires: State Database of New Hires – reduced the overall improper payment rates in state UI programs between 2004-2013 (Greer and Bullock 2018). The administrative benefits offered by automation of UIP claims processing via Information and Communication Technologies (ICT) included the reduction of 'racialized' administrative errors attributable to personal interactions (Compton, et al. 2022). This logic leads to the first hypothesis.

H1: IT Modernization Reforms Reduce Overall Program Error Rates.

Although the performance benefits of IT modernization have been advocated by both governments and academics, a rising tide of scholarship emphasizes the lack of impartiality, or neutrality, associated with algorithms. Bovens and Zouridis (2002) argue that although technology reduces the discretionary power of street-level bureaucrats, it also introduces administrative discretionary by IT system designers and experts, as well as legal policy staff. The resulting standardized modules and algorithms have distributional consequences that create bias, reduce fairness, and exacerbate inequalities arising from administrative decision-making (Eubanks 2018;

Ledford 2019; Patty and Penn 2023). Such distributional consequences are attributable to automating technologies prioritizing efficiency goals at the expense of other core public values, including social equity (Schiff, et al. 2022). This is because ICT-enabled automation in the public sector is intended to yield efficiency and productivity gains (Shrum, et al. 2019: 9). This emphasis on administrative efficiency vis-a-via administrative fairness is borne out by research showing that automated systems perpetuate systematic errors of exclusion of certain groups against the others (e.g., Aman-Rana, et al. 2023; Young, et al. 2021). Peeters and Widlak's (2023) evidence from the Dutch daycare benefit scandal reveals that an emphasis on program efficiency concerns can result in the deployment of automated systems that lack adequate checks for fairness and accuracy. In turn, perpetuating social inequities through systematic errors of exclusion.

These concerns with waste, fraud, and abuse resulting in Type I program administration errors are also germane in many other governance settings, including state administration of unemployment insurance benefits. Based on the state UIP data analyzed in this study among IT modernization reform adopting states, Type I program benefit overpayment (agency) errors constitute an annual average of $38.13 million per state UIP, which represents 4.48% of average total program benefits.[1] IT Modernization projects undertaken by state UIP agencies are primarily motivated by the desire to reduce benefit overpayment (Type I) errors. Unemployment insurance programs are singled out as one of the U.S. federal programs with the highest level of improper payments since 2018 (Office of Management and Budget **nd**). U.S. federal funding for IT modernization projects is tailored to create system reforms designed to identify such Type I benefit overpayment errors (National Employment Law Project 2012). Due to an emphasis on increasing program efficiency, IT modernization reforms aim to reduce Type I program errors in absolute

[1] The state-month average amount of Type I program benefit overpayment errors in June 2010 constant-dollars is $3,177,671, while the state-month average total benefits are $ 73,000,000 ($73 million).

terms, but also relative to Type II program errors involving the denial or underpayment of benefits to eligible claimants. Simon-Mishel, et al. (2023) find that state UIP agency officials view the distributional consequences of IT modernization reforms not so much as "*…. a negative sign of reduced claimant access to benefits, …..*" (Simon-Mishel, et al. 2022: 36), but rather as "*…. an improvement in issue detection, and that many of these cases would have been found to be overpayments later.*" (Simon-Mishel, et al. 2022: 37).[2] This logic yields the third hypothesis.

H2: IT Modernization Reforms Reduce Efficiency-Based Type I Program Error Rates.

How Task Complexity Shapes the Impact of Administrative Reforms

Task complexity is defined as "*the amount of specialized knowledge necessary to resolve uncertainties about the consequences of action.*" (Gormley 2014: 21). Task complexity reflects information interrelationships (Campbell 1984; Steinmann 1976) and information load (March and Simon 1958: 139-141). Therefore, more complex tasks entail greater "*…. information load, information diversity, or rate of information change*." (Campbell 1988: 43).[3] Because more complex tasks require greater coordination due to information acquisition from various sources (March and Simon 1958: 182-189), administrators must expend greater effort towards tasks of high complexity compared to those of low complexity (Allegrini, et al. 2021; Chen, et al. 2024). In the case of state

[2] The Michigan Unemployment Insurance Agency's Michigan Integrated Data Automated System (MiDAS) that was launched in 2013 was intended to reduce Type I benefit overpayment payment errors by state officials, especially fraud detection (Michigan Office of the Auditor General 2016: 21). Due to such administrative priorities, many unemployed Michigan citizens experienced wage garnishment or seizure of income tax refunds, which sometimes resulted in personal bankruptcy (Roberts 2024).

[3] This general definition of task complexity is compatible with more stylized definitions rooted in heterogenous service needs among the clientele population (Andrews, et al. 2005; Odeck and Akadi 2004).

UIPs, task complexity can be viewed as cases "*subject to additional rules and requirements, making their administration more complex*." (Young, et al. 2023: 10).

Highly complex administrative tasks, therefore, make attaining quality performance outcomes harder to attain (Andrews, et al. 2005; Odeck and Akadi 2004). Because complex tasks are inherently more challenging when it comes to arriving at correct administrative decisions, IT reforms confer disproportionately greater performance benefits for highly complex tasks vis-à-vis low complexity tasks. Because task complexity pertaining to the processing of UIP caseloads increases the likelihood of administrative errors (Young, et al. 2023), IT modernization reforms can assist in alleviating such problems by reducing the overall program error rate since they are positively associated with claims that are slower to process (Wenger and Wilkins 2009).

Innovations in IT not only reduce information search costs, but also enhance information sharing and effective coordination among administrative units (Hu and Kapucu 2016). IT modernization can offer performance benefits for highly complex, albeit routinized tasks reflecting low uncertainty (Bullock, et al; 2022). Performance benefits attributable to IT modernization will thus be most acutely felt when agencies face complex task environments. In turn, IT modernization reduces performance gaps between high complex task workloads versus low complex task workloads. For example, state UIP agencies with modernized IT systems and non-modernized states show notable differences in error rates in work search activity verification (Simon-Mishel, et al., 2022; Wentworth & McKenna 2015). These performance differences are largely due to the imbalance of information between claimants and the agency that makes it difficult to accurately verify whether claimants are actively seeking work (U.S. Government Accountability Office, 2018: 19-22). Modernized IT systems automate eligibility-related documentation and verification, particularly improving the caliber of complex tasks. This logic leads to the third hypothesis.

H3: Modernization Reforms Reduce Overall Program Error Rate Differences Between High and Low Task Complexity Caseloads.

Because IT Modernization reforms focus on improving program efficiency aspects such as processing speed, preventing wasteful spending, and the like (Cordella and Tempini 2015; Schiff, et al. 2019), the resulting performance benefits will be acute for Type I program error rates involving overpayments to unemployed claimants when agencies have high task complexity caseloads. These benefits should occur for reducing task complexity differentials involving Type I program error rates in absolute terms, based on the volume of paid claims' transactions sampled via BAM. In addition, these conditional performance benefits should be more acutely observed for reducing Type I program error rates relative to Type II program errors. IT enhancements will be more effective at closing the performance gap between high and low complexity task workloads involving the reduction of benefit overpayments (Type I program errors) compared to reducing social inequities (Type II program errors) resulting from underpayment errors and outright denial of government benefits to program-eligible clients. Anecdotal evidence suggests that the replacement of human labor with self-service web platforms has often limited accessibility to services for minorities (Miami Workers Center v. Florida Department of Economic Opportunity, Division of Workforce Services 2015). These automated efforts at data acquisition and storage often lack contextual interpretation of claimants' needs beyond the pre-programmed list of information that is processed online, thus limiting accessibility for eligible program clients (Cordelia 2006; Elyounes 2021). This logic yields the final hypothesis.

H4: Modernization Reforms Reduce Type I Program Error Rate Differences Between High and Low Task Complexity Caseloads.

DATA AND ANALYTICAL STRATEGY

The empirical design is comprised of 30 state panels from 28 states where IT reforms where adopted/instituted by state UIP agencies within the January 2001—June 2022 sample period under investigation (see **Figure 2** below for information on states and sequences of IT reform adoptions).[4] Both New Mexico and Nebraska each have two separate panels since they adopted two IT modernization reforms during the sample period.[5] The basis for analyzing only IT reform adopting state UIP agencies is that it provides a comparable, meaningful baseline to compare adopting state UIP agencies' performance both prior and following the adoption of these IT reforms. Inclusion of non-adopting state UIP agencies in the pre-adoption baseline conflates the organizational adaptation process pertaining to IT reforms with non-IT reform state UIP agencies. The time unit of the performance is month-year (monthly observations) which permit granular analysis of organizational adaptation to IT modernization reforms reflected by program error rates.

Dependent Variables: State UIP Program Error Rates

Effective administration is defined in this study as agency-induced program error rates when administering claims for unemployment insurance benefits by unemployed citizens. This focus is restricted to only agency-induced program errors since these are the result of actions taken by administrative actors; whereas, program errors resulting from other sources do not reflect ineffectual agency behavior in the administration of these programs.[6] The data employed to

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[4] Montana adopted/instituted IT reform in April 2001, and thus omitted from the sample since it lacks pre-adoption observations.

[5] New Mexico adopted IT reforms in November 2002 and March 2013, while Nebraska adopted these reforms in July 2007 and July 2015.

[6] For purposes of this investigation, *agency-responsible errors* are defined as errors that the audit process determines to be erroneous <u>and</u> also the responsibility of the state UIP agency. Errors solely attributable to other parties are omitted from our program error rate calculations. Following the U.S. Department of Labor instruction of coding responsible parties in the BAM survey, list of agency actions that BAM auditors code as 'agency errors' means that the state UIP agency either had sufficient document to identify or had identified the issue prior to the sample selection but did not resolve the issue, official procedures/forms had not been properly followed by state or provided incorrect information or instructions. What these agency errors do not

construct the various dependent variables measuring alternative program error rates in the administration of state UIP program errors comes from the Benefit Accuracy Measurement (BAM) survey sample employed by the U.S. Department of Labor. BAM survey collects and reports program integrity by states every year, which is one of the five 'core performance measures,' including payment timeliness, program integrity, appeals timeliness and quality, tax timeliness and quality, and reemployment rate. Corrective Action/Continuous Improvement Plans must be submitted for states whose performance did not meet the established criteria for the annual measurement period (U.S. Department of Labor 2002: I-9). Among the core measures, program integrity encompasses the overall accuracy and legitimacy of the program's administration, making it a comprehensive metric for assessing administrative performance.

The weekly BAM survey sampling data are employed. These data cover program errors attributable to state UIP agencies (denoted in the numerator of the measures defined below), as well as the number of total cases sampled in each respective BAM survey (denoted in the denominator of the program error rate measures defined below). State BAM samples are randomly selected from the populations of UIPs (including combined wage claims), UCFE (Unemployment Compensation for Federal Employees), and UCX (Unemployment Compensation for Ex-Servicemember) payments and determinations denying eligibility issued by the state each week. This weekly sampling interval begins at midnight Sunday and runs until 11:59 p.m. Saturday. A limitation of the BAM survey data for time series analysis is that the weekly sample for each state is extremely small (range from fourteen cases per week in the ten states with the smallest number of

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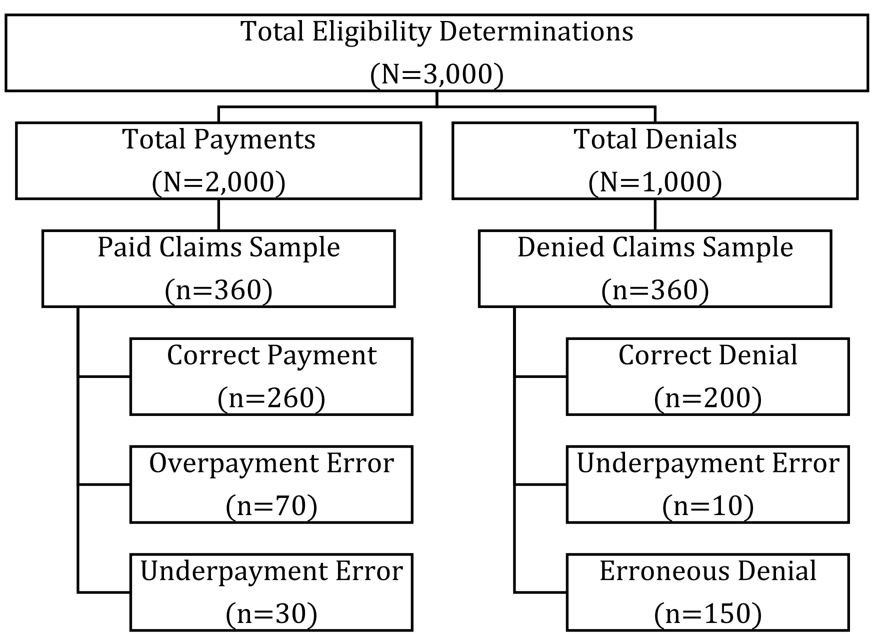
include are when official procedures had been followed while other parties (e.g., claimants, employers, other state UIP agency) are solely responsible for the error (*Source: U.S. Department of Labor 2013. UI Benefit Accuracy Measurement Operations Guide (3rd Edition).* ***Appendix A. Paid Claims Data Elements and Definitions & Appendix B. Denied Claims Data Elements and Definitions.*** *https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2013/UIPL_16_13.pdf).*

claims to twenty cases in the other states of our sample period). To ensure sufficient statistical power while preserving sufficient temporal variation, these data are temporally aggregated up to monthly time intervals. The BAM survey comprises two distinct parallel weekly samples: Paid Claims (i.e., unemployed citizens granted UIP benefits) and Denied Claims (i.e., unemployed citizens denied UIP benefits). The accuracy of these paid and denied claims is assessed through a comprehensive audit of these cases to ensure compliance with all monetary, separation, and other non-separation eligibility requirements, namely the active job search for "suitable work" and "able and available" criteria (U.S. Department of Labor 2013: 1-3).

As illustrated in **Figure 1**, in the paid claims sample, there can be three different outcomes: correct payment, overpayment error, and underpayment error. In the sample of denied claims, there can also be three different outcomes: correct denial, underpayment error (e.g., the denial decision was accurate for some weeks but erroneous for others), and erroneous denial. See **Appendix A** for further details on federal coding instructions for each category of outcomes.

FIGURE 1

Hypothetical Illustration of BAM Survey Sample of State UIP Program Decisions



Each of the dependent variables representing rates of total program errors, Type I program errors, and the proportion of Type I program errors to Total Program Errors are numerically defined below based on sample-weighted program error rates, with Type I program error rates based solely on the Paid Claims BAM Sample:

$$\mathit{Total\ Error\ Rate} = \overbrace{\left(\frac{\#\,\mathit{Overpayment\ Errors}}{\#\,\mathit{Paid\ Claims\ Sample}}\right)}^{\mathit{Type\ I\ Error Rate}} \tag{1}$$

$$+ \overbrace{\left(\frac{\#\,\mathit{Underpayment\ Errors}}{\#\,\mathit{Paid\ Claims\ Sample}}\right) + \left(\frac{\#\,\mathit{Erroneous\ Denial\ Errors}}{\#\,\mathit{Denied\ Claims\ Sample}}\right) + \left(\frac{\#\,\mathit{Underpayment\ Errors}}{\#\,\mathit{Denied\ Claims\ Sample}}\right)}^{\mathit{Type\ II\ Error\ Rate}}$$

$$(\mathit{Absolute})\,\mathit{Type\ I\ Error\ Rate} = \left(\frac{\#\,\mathit{Overpayment\ Errors}}{\#\,\mathit{Paid\ Claims\ Sample}}\right) \tag{2}$$

$$\mathit{Relative\ Type\ I\ Error\ Rate} = \frac{\mathit{Type\ I\ Error\ Rate}}{\left[\mathit{Type\ I\ Error\ Rate} + \mathit{Absolute\ Type\ II\ Error\ Rate}\right]} \tag{3}$$

The first dependent variable, *Total Program Error Rate* is a weighted sum of the proportion of overpayment and underpayment errors in the paid claims sample and the proportion of underpayments and erroneous denial errors in the denied claims sample. The second dependent variable, *Absolute Type I Program Error Rate* is a weighted sum of the proportion of overpayment errors in the paid claims sample. The third dependent variable, *Relative Type I Program Error Rate*, is the proportion of absolute Type I program error rate in relation to the total program error rate (*Type I Error Rate + Type II Error Rate*).

Organizational Adaptation and Task Complexity Covariates

The *Organizational Adaptation* variable is defined as a time counter variable that equals “0” before the activation of a new automated system for state *i*, month $t-\iota$ (where $\iota \geq 0$); “1” for the first month of the new automated system is in effect for state *i*, month t+1; ……….; and “*m*” for state *i* in m^{th} month that the new automated system has been in effect for state *i* year *t*. For the purposes of this study, the first year-month of each state's introduction of the new automated system is determined by the time when the new automated system was adopted and went 'live' (i.e., instituted). This point indicates when the system began to influence the agency's operations.

In this study, we test whether organizational adaptation to IT reforms, as reflected in UI program error rates, exhibits differential effects by task complexity. The two main factors contributing to information load and variety in the eligibility determination process are interstate claims and seeking a different occupation. The first variable, *Task Complexity: Interstate Claims* is a categorical variable indicating '0 (Low Task Complexity)' for values equal to or below 25th percentile, '1 (Moderate Task Complexity)' for values greater than 25th percentile and less than 75th percentile, '2 (High Task Complexity)' for values equal to or greater than 75th percentile. *Task Complexity: Interstate Claims*, captures the task complexity of a state UIP agency in a given month, measured as the weighted proportion of interstate claims in the paid and denied claim samples for *Total Program Error Rate* models and *Relative Type I Program Error Rate* models. For *Absolute Type I Error Rate* models, it includes only the paid claim sample. Processing interstate claims is more complex because it involves coordination with multiple state UIP agencies (Esterle 1996). Next, *Task Complexity: Seeking Different Occupation* captures the task complexity resulting from claimants seeking a different occupation. This measure is also a categorical variable indicating '0 (Low Task Complexity)' for values equal to or below 25th percentile, '1 (Moderate Task Complexity)' for values greater than 25th percentile and less than 75th percentile, '2 (High Task Complexity)' for values equal to or greater than 75th percentile. Eligibility assessments for these cases requires additional information search and specialized knowledge as they are subject to special rules (U.S. Department of Labor 2023) as well as frequent coordination with state employment service agency (Trutko, et al. 2022: 49-50), leading to higher complexity. Previous research indicates that for every additional 100 claimants seeking new occupations, an additional 4.5 administrative errors occur (Young, et al. 2022).

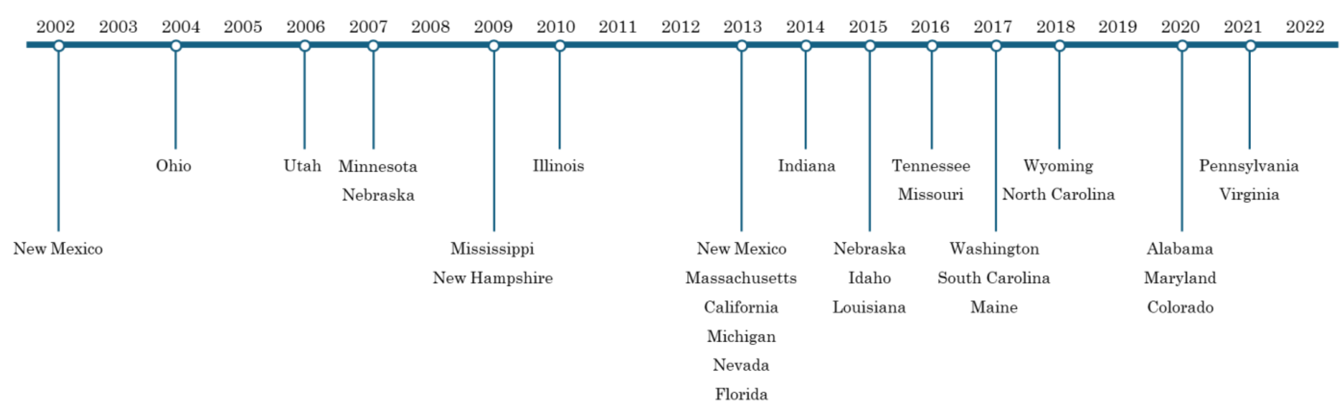
Control Covariates

Additional control variables are included to account for both agency and claimant characteristics that influence program error rates attributable to state UIP agencies. The control covariate *Democratic Governor* is a binary indicator of '1' if the governor is a democrat and *Republican Governor* is a binary indicator of '1' if the governor is a republican in a given state-month. These two measures account for political influences on agency priorities regarding absolute and relative Type I error rates vis-à-vis Type II error management. *Workload* is measured as the log-transformed number of initial claims. A greater workload is expected to be positively associated with total program error rates as well as absolute and relative Type I error rates. *Automation Rate*, measured as the percentage of claims filed through internet as opposed to in-person, telephones, and mails per state-month, is expected to be negatively associated with program error rates, as it reduces the possibility of human error throughout the administrative process. *Agency Budget* is measured as the log-transformed total administrative expenditure of the state UIP agency for a given fiscal year. This covariate captures resource-based investments that might affect an agency's performance in terms of payment accuracy. *State Benefit Generosity* is measured as the percentage of claimants whose regular weekly benefit amount (WBA) for a period of total unemployment is the maximum under the state law. This variable is expected to be positively associated with program error rates because higher benefit generosity often correlates with more lenient UI policies. *State Unemployment Rate* is measured as the percentage of seasonally adjusted unemployment rates, reflecting the demand for social benefits in a given state-month. This control covariate is expected to be positively correlated with program error rates since rising unemployment should bear greater workload that the state UIP agency has to handle than compared to when economic conditions reflect lower levels of unemployment. *Administrative Capacity* measures the state UIP agency's administrative quality, operationalized as the average real dollar amount of salary for administration and supervision of the UI program per position in each state for a given fiscal year.

This control variable is expected to be negatively associated with program error rates. *Proportion of Non-White Claimants*, *Proportion of Female Claimants*, and *Proportion of Claimants Aged Under 25 or Above 65* are claimant demographics likely to be positively correlated with program error rates.

In addition, unobserved heterogeneity at the state, year, and adoption-year cohort reform levels is accounted for by a distinct set of binary indicator covariates for each level.[7] These set of unit effects are intended to control for systematic differences across states, over time, and the temporal sequence of IT modernization reform adoptions that might confound our relationships of interest. Regarding the latter set of controls, states institute IT reforms at various points in time (see **Figure 2** below). Therefore, IT modernization reform adoption year cohort unit effects account for the highly irregular, variable sequence of when states adopt such reforms, and its corresponding heterogeneous impact on agency performance (see Wooldridge 2021). This set of binary indicators representing adoption year-cohort reform unit effects equal 1 when state *i* institutes an IT modernization reform in year *T* in the precise month (*t+1*), and beyond (*t+m*), that the IT modernization reform is adopted/instituted, and equals 0 otherwise.

FIGURE 2. Timeline of IT Modernization by State UIP Agencies, 2002-2022



[7] These covariates are operationalized as a series of respective state *i* and year *T* binary indicators, plus a series of adoption year cohort reform binary indicators that equal 1 when state *i* institutes an IT modernization reform in year *T* and month *m* when it is instituted, and 0 otherwise.

Methodology

The statistical model employed to evaluate the core hypotheses relating to state UIP program error rates in response to IT modernization reforms involves a semi-parametric estimating equation of the general form:

$$\boldsymbol{y}_{i,t} = \overbrace{\boldsymbol{g}\left(\boldsymbol{x}_{i,t}\right)}^{\textit{Organizational Adaptation}} + \overbrace{\beta_k \boldsymbol{Z}_{k\,i,t}}^{\textit{Additional Controls}} + \overbrace{\gamma_i \boldsymbol{S}_i + \lambda_T \boldsymbol{T}_T + \eta_{i,T} \boldsymbol{C}_{i,T}}^{\textit{Unit Effects}} + \varepsilon_{i,t} \tag{4}$$

where the program error rate outcome measures are represented by the *Total Error Rate*, Absolute *Type I Error Rate*, Relative *Type I Error Rate* for state *i* in month *t* ($\boldsymbol{y}_{i,t}$) is nonparametrically modeled as a function of organizational adaptation to the institution of IT reforms that is heterogenous across variable task complexity caseloads being processed by state UIP agencies (*Task Complexity Caseload* covariates) [$\boldsymbol{g}(\boldsymbol{x}_{i,t})$], plus a linear-parametric function of control covariates ($\boldsymbol{Z}_{k\,i,t}$), plus state ($\boldsymbol{S}_i$), year ($\boldsymbol{T}_T$), and adoption year-cohort reform unit effects ($\boldsymbol{C}_{i,T}$), with a regression disturbance term ($\varepsilon_{i,t}$). A cross-validation criterion reveals that a single (one) knot is optimal in the subsequent nonparametric B-Spline estimation of the statistical models.[8]

The semi-parametric statistical modeling approach is advantageous in modeling the conditional dynamics of organizational adaptation to administrative reforms. A wide array of competing models of organizational adaptation or learning exist, thus making it hard to discern the correct functional form *ex ante* to model estimation. In turn, this increases the likelihood of generating biased estimates of organizational adaptation. Further complicating matters, functional forms might vary considerably based on model specification and estimation sample choices. As a result, the timing of the optimal or 'peak' performance attributable to reform-based adaptation might be non-constant through time. To arrive at valid estimates of organizational adaptation that

[8] Model estimation is conducted using Stata 18's ***npregress series*** command function.

neither rely on correct functional form nor distributional assumptions, these relationships are estimated from the observed data in a nonparametric manner.

Although nonparametric estimation offers clear advantages, these come at a cost when seeking to estimate models with multiple covariates and complex nonlinear relationships due to the 'curse of dimensionality' that is encountered when estimating several parameters (covariates) over a sparse observed data region (e.g., Geenens 2011: 32).[9] A hybrid semi-parametric modeling strategy overcomes this dilemma by estimating heterogenous organizational adaptation nonparametrically using B-spline series regression, while estimating all control covariates (unit effects and additional controls) using parametric linear methods.[10] This approach to modeling organizational adaptation behavior is both practical and appropriate when the temporal process being modeled involves high frequency data that contains a large number of time points that make modeling monthly unit effects both problematic and ill-advised.[11]

EMPIRICAL EVIDENCE

The hybrid semi-parametric regression model estimates predicting agency-induced (1) overall program error rates, (2) Absolute Type I program error rates, and (3) Relative Type I program errors rates appear in **Models 1—3** appear in **Table 1.** Brief inspection of the control covariates in the linear-parametric segment of these statistical model estimates reveals that these

[9] Given the data design, this requires estimating 251 (t–1) monthly unit effect parameters. Estimating this high volume of parameters yield not only substantial efficiency loss, but also risk data overfitting due to the numerous sparse data regions being accounted for by individual estimated parameters.

[10] B-spline approaches to nonparametric estimation are especially well-suited in applications, where both intensive and repeated numerical computations are required of the data (Kirkby, et al. 2023: 76).

[11] This B-spline estimation involves estimating 1,512 (252 × 6) cross-product derivative combinations of 252 post-IT reform monthly cases and three different categories for each of the two task complexity covariates.

program error rates are not statistically different between Republican versus Democratic governors, nor in relation to the Non-Partisan/Independent governor baseline. The *Automation Rate* is positively associated with overall program and absolute Type I error rates, but not relative Type I error rates. Although the relative reliance on automated processing affects program error rates, it does not affect the relative balance between efficiency and social equity captured by relative Type I program error rates. *State Benefit Generosity* has a positive statistical association with all three program error rate measures, that is stronger with respect to higher administrative inefficiency resulting from Type I program overpayment errors. In turn, this evidence indicates a tension between efficiency and social equity since, on average, programmatic waste emanating from state UIP decisions is a byproduct of offering more generous social insurance benefits. Increases in the *State Unemployment Rate* are positively correlated with overall program error rates, and not with Type I program errors relating to waste induced by agency decision errors. The evidence relating to demographic characteristics is mixed, with the *Proportion of Non-White Claimants* being positively associated with total program error rates, while the *Proportion of Female Claimants* is positively associated with Type I program error rates.

To better understand the nonparametric estimates evaluating the primary hypotheses centered on organizational adaptation, these estimates are presented graphically in **Figures 3** and **4**. This approach to presenting and interpreting **H1**–**H4** is necessary for these nonparametric models since the tabular regression estimates displayed in **Table 1** constitute only average coefficient estimates, and hence, cannot ascertain the nature of organizational adaptation through time. Moreover, the nonparametric estimates involving the conditional task complexity hypotheses (**H3** and **H4**) are manifested through cross-product (interactive) effects between the IT modernization reform covariate and the discrete, categorical task complexity covariate. **Figure 3** contains the organizational adaptation estimates on total program error rates, based on IT modernization reforms adopted by state UI agencies, for the five years (60 months) following the institution of

TABLE 1

Hybrid Semi-Parametric Models of Agency-Induced Administrative Program Errors: State Unemployment Insurance Benefit Program Error Rates (2002-2022)

	M1 Total Program Error Rates	M2 Absolute Type I Error Rates	M3 Relative Type I Error Rates
Organizational Adaptation (Post-IT Reform Time Trend)	**−0.06E-02****	**−0.089E-02*****	**−0.002**
	(0.03E-02)	**(0.015E-02)**	**(83.455)**
Task Complexity (Base = Low Task Complexity)			
Interstate Claims			
Moderate Task Complexity	**−0.002E-01**	**−0.004****	**−0.014***
	(0.003)	**(0.002)**	**(0.008)**
High Task Complexity	**−0.004**	**−0.001**	**−0.015**
	(0.005)	**(0.003)**	**(0.017)**
Seeking Different Occupation			
Moderate Task Complexity	**0.012*****	**0.005****	**−0.011**
	(0.003)	**(0.002)**	**(0.009)**
High Task Complexity	**0.020*****	**0.011*****	**0.020***
	(0.004)	**(0.003)**	**(0.011)**
Democratic Governor	0.020	0.005	−0.061
	(0.014)	(0.008)	(0.038)
Republican Governor	0.016	0.008	−0.049
	(0.014)	(0.008)	(0.038)
Workload	0.009**	0.003	−0.001E-01
	(0.004)	(0.002)	(0.009)
Automation Rate	0.070***	0.047***	0.009
	(0.010)	(0.007)	(0.022)
Agency Budget	0.008E-08***	0.003E-07***	−0.003E-09
	(0.002E-08)	(0.071E-08)	(0.017E-07)
State Benefit Generosity	0.039*	0.054***	0.147***
	(0.022)	(0.014)	(0.039)
State Unemployment Rate	0.004**	0.003E-01	−0.002E-01
	(0.001)	(0.008E-01)	(0.003E-01)
Administrative Capacity	−0.004E-05	−0.047E-05***	−0.045E-05
	(0.002E-04)	(0.016E-05)	(0.051E-05)
Proportion of Non-White Claimants	0.043***	0.012	−0.011
	(0.008)	(0.010)	(0.017)
Proportion of Female Claimants	−0.002	0.020**	0.065***
	(0.010)	(0.009)	(0.023)
Proportion of Claimants Aged Under 25 or Above 65	−0.018	0.018	0.007
	(0.014)	(0.017)	(0.035)
State—Fixed Effects	YES	YES	YES
Year—Fixed Effects	YES	YES	YES

Adoption Year Cohort Unit Effects	YES	YES	YES
Total Number of Observations[12]	7,000	7,262	6,771
Post-IT Modernization Reform Observations	2,651	2,871	2,569

NOTES: Bootstrapped standard errors (1,000 Replications) reported in parentheses. **Boldface type** entries are nonparametric B-spline estimates. Regular typeface entries are linear (OLS) estimates. *Task Complexity* is a categorical variable indicating '0 (*Low Task Complexity*)' for values equal to or below 25th percentile, '1 (*Moderate Task Complexity*)' for values greater than 25th percentile and less than 75th percentile, '2 (*High Task Complexity*)' for values equal to or greater than 75th percentile. * $p \leq 0.10$ ** $p \leq 0.05$ *** $p \leq 0.010$

these reforms. The unconditional organization adaptation estimates displayed in **Figure 3A** uncover an average 3.21% decline (18.85% − 15.64%) in total program error rates over 60 months when evaluating **H1**. This improvement in reducing agency total program error rate is 23.94% of a one standard deviation of this outcome variable [(3.21%/13.411%)*100].

The conditional organizational adaptation effects offer mixed support for **H3** with respect to task complexity involving interstate benefit claims (**Figure 3B**), as well as those task caseloads involving claimants seeking different occupations (**Figure 3C**). The former results appearing in **Figure 3B** in an imprecisely estimated 1.85% decline in the performance gap in total program error rates between high task complexity and low task complexity caseloads during the 60 months following IT reforms are instituted. The latter estimates appearing in **Figure 3C** represent a 3.64% drop in this performance gap during this same time frame. This evidence highlights the important benefits associated with IT reforms for reducing overall program error rates by narrowing the performance gap between more and less challenging processing of caseloads consistent with **H3**.

[12] Sample sizes vary in **Models 1**, **2**, and **3** due to the nature of the measures used for the dependent variable in each model. Model 1 (Total Program Error Rate Model) is estimated based on 7,000 state-month cases, due to 262 missing observations in the denied claims sample that were excluded by the U.S. Department of Labor due to insufficient sampling. Model 3 (Relative Type I Program Error Rate Model) is estimated based on 6,771 state-month cases, or 262 + 229 fewer state-month observations, due to 229 state-month cases where the denominator of the dependent variable (Total Program Error Rate) is 0.

FIGURE 3

Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)

FIGURE 3A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL 1])

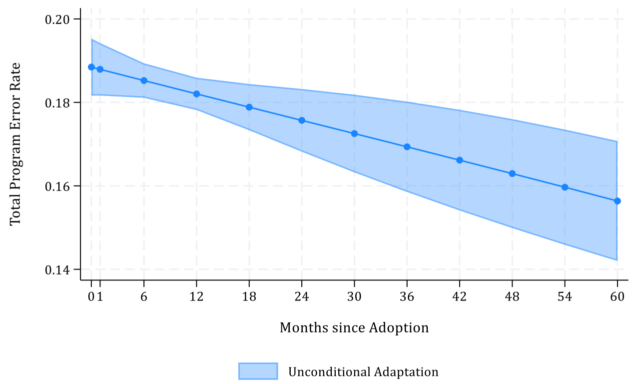


FIGURE 3B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL 1])

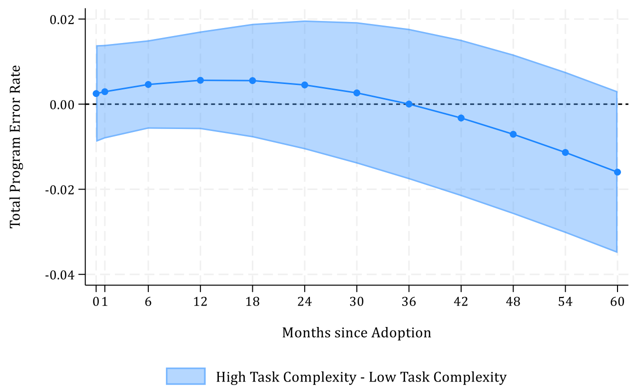


FIGURE 3C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL 1])

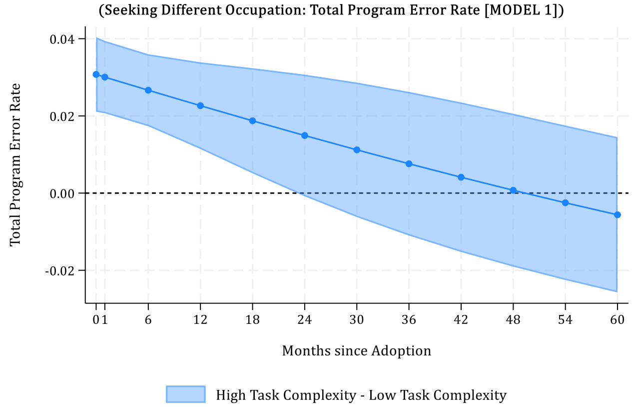


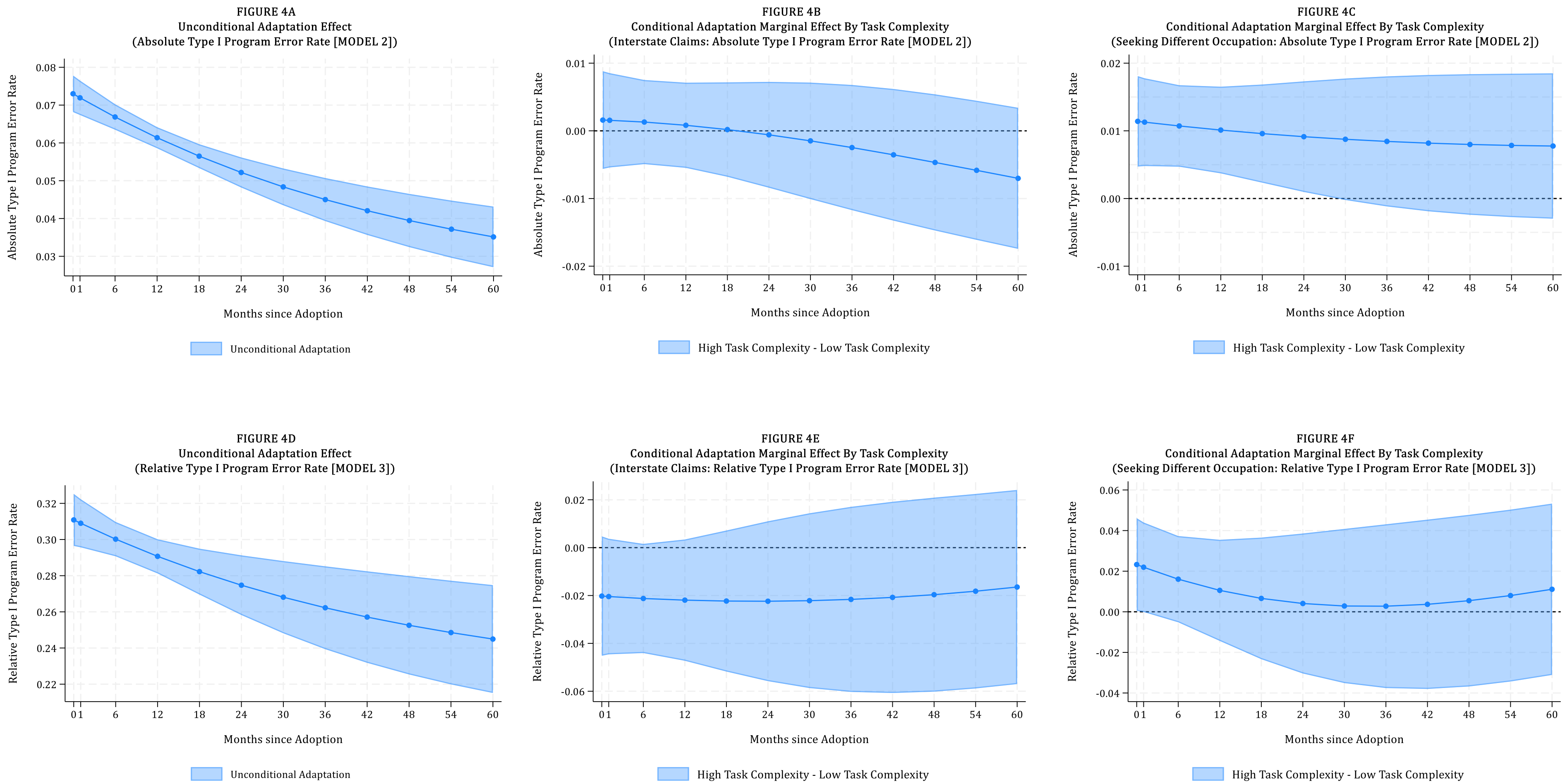
Figure 4 contains the organizational adaptation estimates from **Models 2** and **3** that analyze both the absolute and relative Type I program error rates. The **Model 2** estimates displayed in **Figures 4A—4C** evaluate **H2** and **H4** with respect to absolute Type I program error rates based on the sample of agency-induced overpayment errors observed in the BAM survey of paid benefit claims processed by state agencies for a given month. Consistent with **H2**, **Figure 4A** estimates of unconditional organizational adaptation reveals that the absolute Type I program error rate declines from an average of 7.30% prior to states instituting IT modernization reforms to 3.51%. This constitutes a substantial improvement in agency performance in terms of a 3.79% decline in the absolute Type I program error rate. The conditional organizational adaptation estimates evaluating the attenuating performance differential between high versus low task complexity caseloads are mixed once again. Although the conditional organizational adaptation estimates involving interstate claims declines through time post-adoption consistent with **H4** (**Figure 4B**), the numerical magnitude is a modest 0.86% over 60 months, while also estimated with considerable imprecision, as evinced by the large confidence intervals. Similarly, the estimated reduction in the difference between the absolute Type I program error rates between high versus low different occupation seeking caseloads displayed in **Figure 4C** is a paltry 0.37% after 60 months following IT modernization. That is, reductions in the performance gap involving differential task complexity of caseload processing only occurs for overall program error rates, and not for efficiency improvements pertaining to Type I program error rates.

The **Model 3** estimates displayed in **Figures 4D—4E** evaluate **H2** and **H4** with respect to relative Type I program error rates based on these errors relative to Type II 'false-negative' errors that either deny or understate benefits for eligible unemployment claimants processed by state agencies for a given month. These estimates provide insight into the consequences of IT modernization on reducing efficiency-oriented agency program errors seeking to prevent wasteful spending (Type I errors) relative to an emphasis on reducing social-equity-oriented agency program errors to limit the number of erroneous denials and underpayments (Type II errors) to citizens seeking unemployment insurance benefits. Support for **H2** is compelling, with an average reduction in relative Type I program error rates, thus reflecting improved program efficiency savings, of 6.59% (31.90% − 24.50%) over the course of 60 months following IT modernization reforms take place. Evidence consistent with **H4** is not obtained from these data. Specifically, neither interstate claims (**Figure 4E:** −0.38% after 60 months) nor different seeking occupation (**Figure 4F**: 2.05% after 36 months) caseload variations are affected in a discernible manner by IT modernization reforms as this set of dynamic conditional organizational adaptation estimates lie somewhere between the larger effects estimated from the total program error rates (cf. **Figures 3B** & **3C**) and meager effects generated from the absolute Type I program error rates (cf. **Figures 4B** & **4C**). Further analyses disaggregating Type II program errors in **Appendix E** reveals that the preponderance of these efficiency-equity tradeoffs result from underpayment errors, and to a lesser extent, erroneous claim denials (see **Figure E1A**, cf. **Figure E2A**; **Figure E1B**, cf. **Figure E2B**).

The estimates reported in the manuscript are generally robust to model specifications that omit control covariates beyond the state, year, and adoption-year cohort reform unit effects to mitigate potential post-treatment bias from some of the control covariates (**Appendix B**); sampling design that include non-IT modernization reform states in the baseline of pre-IT modernization reform states (**Appendix C**); and sampling design omitting both the second IT modernization reforms for Nebraska and New Mexico, plus the COVID pandemic era (**Appendix D**). The restricted model estimates that exclude control covariates to avoid potential post-treatment bias in the estimates of organizational adaptation resulting from IT reform (**Appendix B**). These estimates are substantively similar in relation to the reported estimates in the manuscript based on the unrestricted model specifications. The estimates from the full sample that includes non–IT reform adopting states (**Appendix C**) are substantively the same to the reported estimates, except for smaller magnitude estimates that exhibit much less precision beyond the first two years after IT

FIGURE 4

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates: Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)



reforms are instituted (t + 24, ….. , t+60) for unconditional adaptation effects across each of the three program error rate dependent variables (**Figures 3A, 4A,** & **4D**; cf. **Figures C1A, C2A,** & **C2D**). These differences reflect the inclusion of non-adopting states in the pre-adoption baseline, which conflate the organizational adaptation process performance effects observed for IT reform states with the performance of non-IT reform states since both are represented in the baseline (t + 0) estimates as a weighted average.

The estimates generated in **Appendix D** that involve omitting panels where states repeat IT reforms (Nebraska 2015 and New Mexico 2013), plus COVID pandemic years (2020-2022) from the estimation sample (**Appendix D**), yield substantively similar estimates to those reported in the manuscript. Finally, a series of models evaluating 'placebo' treatments pertaining to IT modernization reform are undertaken to evaluate alternative mechanisms that might be the source of performance changes other than institution of IT modernization reforms (see **Appendix F**).[13] The sensitivity of these 'placebo' treatment test results are evaluated restricting the sample of observations to only IT reform pre-adoption treatment (i.e., excluding the IT reform 'adoption' as a potential confounder/control covariate) in **Models F1–F3** (**Figures F1** & **F2**), as well as an unrestricted sample of observations that includes IT reform 'adoption' counter trend as a linear covariate in **Models F4–F6** (**Figures F3** & **F4**).[14] The latter approach ensures against false-positive test results due to common correlation between the placebo and actual treatment that does not reflect confounding (Eggers, et al. 2024: 1115). The results of this analysis appear in **Appendix F** —

[13] These tests use the project start date of these IT reforms as a 'placebo' treatment since it occurs anywhere from one year (12 months) to 12.17 years (146 months) prior to the 'adoption' treatment when IT reforms are instituted into service [Median = 3.92 years (47 months), 25th Percentile: 2.67 years (32 months), 75th Percentile: 4.92 years (59 months)].

[14] This latter approach ensures against false-positive test results due to common correlation between the placebo and actual treatment that does not reflect confounding (Eggers, et al. 2024: 1115).

excluding the IT reform adoption covariate as a statistical control (**Figures F1** & **F2**), and also including this variable (**Figures F3** & **F4**). The findings from these tests demonstrate support for the IT reform adoptions that occur at the time of instituting these reforms into the practice of administration. Specifically, the 'placebo' treatments indicate an unconditional surge for each of the program error rates following the IT modernization project start date, followed by a decline back to pre-start date levels (see **Figures F1A, F3A**; **F2A, F4A**; and **F2D, F4D**). The conditional estimates uncover either a surge (as opposed to a hypothesized decline) in the task difficulty differential in several instances (e.g., **Figures F2B, F2F**), no effect in other instances (**Figures F2E, F4B**), or a short-lived transitory effect (**Figure F3B, F4C**). The lone instances where any sustained decline occurs (**Figures F1B, F2C**) occur when the actual treatment is not specified in the regression model specification, and hence, are susceptible to false-positive test results (Eggers, et al. 2024: 1115)**.**

DISCUSSION

Quality decision making in the administration of government benefits is crucial since it not only ensures the efficient use of public funds, but also ensures that eligible citizens receive the government assistance that they merit. Minimizing errors in government programs has been a top executive agenda at both federal and state levels for the past decade (Greer and Bullock 2018). Given this priority, IT modernization reforms seek to improve administrative performance by increasing both effectiveness and efficiency in program delivery. Yet, a rising tide of scholarship emphasizes the lack of impartiality, or neutrality, associated with information technology in government administration (Bovens and Zouridis 2002), and more recently with algorithms employed in bureaucratic policymaking (Patty and Penn 2023). Further complicating the promise of IT-driven reforms is the fact that adopting new technology is often difficult, thus requiring organizations to adapt their practices to fully realize their potential benefits and enhancing performance outcomes through the organizational change (Repenning and Sterman 2002).

This study departs in two novel ways from existing studies analyzing how administrative reform can influence administrative performance. First, organizational adaptation to IT modernization reforms is analyzed, thus providing a nuanced understanding of dynamic performance changes over time absent from studies focused on static before-and-after difference comparisons. Second, this study seeks to contribute to the burgeoning area of research by assessing dynamics in the administrative performance following IT-driven reforms with conflicting goals in the public sector. The statistical evidence reveals that IT modernization reforms reduce overall and Type I program error rates. This study's evidence reveals that IT reforms, in general, yield greater performance benefits for improving efficiency relative to social equity consistent with research emphasizing that technological forms of governance are non-neutral in terms of failing to improve social equity (De Boer and Raaphorst 2023; Schiff, et al. 2021, see also, Patty and Penn 2023). These benefits generally do not extend to improving the processing efficiency unemployment insurance benefit claims between states with high versus low difficulty task complexity caseloads. In turn, this suggests that the broad, systemic nature of technology-driven administrative reforms results are restricted to general or overall performance improvements.

On a broader level, the evidence corroborates existing claims that technological-based administration is inherently non-neutral since program efficiency is improved at the expense of program social equity in relative terms. Further, the evidence also is consistent with the notion that reducing inefficiency in program administration is often in tension with social equity concerns (Bozeman 2008; Yates 1982). Modeling dynamic adaptation in response to agency-wide technological reform offers a novel approach for future investigations into the benefits and costs associated with the government's use of information technologies and algorithms in the administrative process. While IT modernization presents significant opportunities for improving the efficiency of government administration, it simultaneously raises concerns about meeting social equity challenges in the administration of government programs.

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APPENDIX DOCUMENT

Organizational Adaptation, Task Complexity, and Effective Administration of Unemployment Programs in the American States

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APPENDIX A: Descriptive Statistics; Information on State UI Agency IT Modernization Reforms, State UIP Program Error Rate Measures, and Task Complexity Measures

APPENDIX B: Sensitivity Analysis, I: Omit Additional Control Variables

APPENDIX C: Sensitivity Analysis, II: Inclusion of Non-IT Adopting States

APPENDIX D: Sensitivity Analysis, III: Omit 2nd IT Modernization Reforms [Nebraska and New Mexico] & COVID Pandemic Years (2020-2022)

APPENDIX E: Analyzing Relative Type I Program Error Rates: Disaggregating Type II Program Errors – Distinguishing Between Underpayment Errors and Erroneous Denial Errors

APPENDIX F: 'Placebo' Treatment Analysis: Use IT Modernization Reform Project Start Date as 'Placebo' Intervention: Both Excluding and Including 'Adoption' Treatment as a Control Covariate (Linear—Parametric) in Semiparametric Models

APPENDIX A:

Descriptive Statistics; State UI Agency IT Modernization Reforms, State UIP Program Error Rate Measures, and Task Complexity Measures

TABLE A1

Descriptive Statistics for Variables Analyzed in Manuscript

Variable	N	Mean	SD	Min	Max	Source
Dependent Variables						
Total Program Error Rate	7,000	0.172	0.134	0.000	1.056	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Absolute Type I Program Error Rate	7,262	0.057	0.085	0.000	0.676	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Relative Type I Error Rate	6,771	0.285	0.262	0.000	1.000	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Organizational Adaptation & Task Complexity Covariates						
Organizational Adaptation (Post-IT Reform Time Trend)	7,000	25.055	44.799	0.000	236.000	Compiled by authors from online sources. A comprehensive list of sources is available upon request.
Proportion of Interstate Claims	7,000	0.109	0.103	0.000	0.786	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Proportion of Claims Seeking Different Occupation	7,000	0.546	0.208	0.000	1.299	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Control Covariates						
Democratic Governor	7,000	0.403	0.491	0.000	1.000	Book of the States. 2002-2022.
Republican Governor	7,000	0.590	0.492	0.000	1.000	Book of the States. 2002-2022.

Ln.Workload	7,000	8.846	1.137	2.833	12.232	ETA-5159 Report. https://oui.doleta.gov/unemploy/DataDownloads.asp.
Automation Rate	7,000	0.511	0.317	0.000	1.000	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Agency Budget	7,000	73,400,000	95,800,000	7,045,456	736,000,000	U.S. Department of Labor. "Resource Justification Model," https://oui.doleta.gov/rjm/
State Benefit Generosity	7,000	0.343	0.137	0.000	0.948	ETA-218 Benefits Rights Experience Report. https://oui.doleta.gov/unemploy/DataDownloads.asp
State Unemployment Rate	7,000	5.590	2.147	1.800	15.900	U.S. Bureau of Labor Statistics. "Local Area Unemployment Statistics. 2002-2022."
Administrative Capacity	7,000	62,115.960	11,585.130	23,198.770	103,441.300	U.S. Department of Labor. "Resource Justification Model," https://oui.doleta.gov/rjm/
Non-White Claimants (%)	7,000	0.630	0.448	0.000	2.000	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Female Claimants (%)	7,000	0.907	0.166	0.250	1.500	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.
Aged Under 25 or Above 65 (%)	7,000	0.316	0.102	0.024	0.925	U.S. Department of Labor. Benefit Accuracy Measurement Survey. 2002-2022. Publicly Available Upon Request.

Information on State UI Agency IT Modernization Reforms

The *Organizational Adaptation* variable is defined as a time counter variable that equals "*0*" before the activation of a new automated system for state i, month t−ι (where ι ≥ 0); "*1*" for the first month of the new automated system is in effect for state i, month t+1; ……….; and "*m*" for state I in mth month that the new automated system has been in effect for state i year t.

For the purposes of the study, the first year-month of each state's introduction of the new automated system is determined by the time when the new automated system went live, as this indicates the point at which the system began to influence the agency's operations. The go-live dates and vendor information of the new automated system in these states were collected by the authors. Major source of information comes from the official website of the UI Information Technology Support Center (http://www.itsc.org/Pages/UIITMod.aspx), which is an organization under the National Association of State Workforce Agencies (NASWA) that provides the status of state UI IT modernization projects since 2013. Sources include news articles, state legislature audit reports, state RFP documents, and from inquiries to the agency's IT unit. A comprehensive list of sources by each state and agency head is available upon request.

The new automated systems adopted by these 29 states—despite being state-initiated and driven reforms (i.e., IT modernization projects)—share the following two key components. The system "uses an application technology that inherently supports (a) web-based services and (b) object-oriented paradigms in combination with a relational database technology (National Association of State Workforce Agencies 2010: 2)." See **manuscript pages 2-3** for more details on these key common features of state UIP agencies' IT Modernization Project and their automated systems. This is due to instances where a single vendor collaborated with multiple states[1], and therefore using the same product developed by that vendor, and/or the states faced common

[1] List of vendors and partner state UIP agencies.

federal incentives to comply with several components in the IT modernization project to be eligible for federal funding (U.S. Department of Labor 2023: VI-1 – VI-3). Therefore, we coded the month as "1" and beyond for the go-live date of the automated system only when the state UIP agency's IT system reform, commonly referred to as the "IT Modernization Project," consisted of these two features. Other minor updates to the existing system were excluded and thus not coded as the launch of a new IT system.

State UIP Program Error Rate Measures

The program error rates for state UIP agencies by state and month were obtained upon request from the U.S. Department of Labor. Each state UIP agencies' Benefit Payment Control (BPC) unit must conduct Benefit Accuracy Measurement (BAM) survey based on sampling estimates generated by weekly sample of UI payments.

[Sample Design & Size] State BAM samples are randomly selected from the populations of UI (including combined wage claims), UCFE (Unemployment Compensation for Federal Employees),

Vendor Name	Partner State UIP Agencies
Accenture	Illinois
Capgemini	Nevada, North Carolina, South Carolina
CSG Government Solutions	Michigan
Deloitte	Colorado, Florida, Massachusetts, Minnesota, Montana, New Hampshire, New Mexico (2002), Ohio, Utah
FAST Enterprise	Washington
Geographic Solutions	Louisiana, Nebraska, Pennsylvania, Tennessee
HCL America	Virginia
KSM Consulting	Indiana
Netacent	Alabama, Idaho
SAGITEC	California, Maryland
Tata Consultancy Services	Maine, Mississippi, Missouri, Nebraska, New Mexico (2013), Wyoming

and UCX (Unemployment Compensation for Ex-Servicemember) payments and determinations denying eligibility issued by the state each week. Both intrastate and interstate claims are included. The accuracy of paid and denied claims is assessed through a comprehensive audit to ensure compliance with all monetary, separation, and other non-separation eligibility requirements, such as active job search and "able and available" criteria (U.S. Department of Labor 2013: 1-3).
The BAM survey is comprised of two distinct parallel weekly samples: Paid Claims (i.e., unemployed citizens granted UIP benefits), and Denied Claims (i.e., unemployed citizens denied UIP benefits). This weekly sampling interval begins at midnight Sunday and runs until 11:59 p.m. Saturday. Allocated paid claims sample sizes range from 7 cases per week in the 10 states with the smallest UIP workloads to 10 cases in the remainder of the states. Several states have chosen to select larger samples. Allocated denied claims sample sizes also range from the same size (U.S. Department of Labor **nd**). To ensure sufficient statistical power while preserving sufficient temporal variation, we aggregated these data up to monthly time intervals.

[Agency Responsible Errors] BAM auditors can determine that a claim contains multiple errors by multiple actors, including state employees, claimants, employers, or third parties. We define agency-responsible errors as any errors for which state UIP agencies are either partially or solely responsible (Data element '**ei4-ErrorRespons**' in the database '**pca_errisu'** is '30', '34', '230'. '234'. '1030', '1034', '1230', or '1234' for the paid claims sample. For the denied claims sample, the data element '**resp**' in the database '**dca_errisu'** is '30', '34', '230', '234', '1030', '1034', '1230', or '1234').

[How the Variables Were Constructed] The first dependent variable, *Total Error Rate* is measured as the sample weighted sum of agency-responsible *Type I Error Rate* from the paid claims sample and agency-responsible *Type II Error Rate* from both the paid and denied claims sample. *Type I Error Rate* is measured as the sample weighted proportion of the number of cases involving an overpayment error in the paid claims sample: $\left(\frac{\#\ \ Overpayment\ Error\ Cases}{Paid\ Claims\ Sample}\right)$.

From the original BAM database, these cases fall into any of the following error codes.

List of Overpayment Error Codes *(Data Element '**ei2-KW Action**' of BAM Paid Claims Accuracy Database **'pca_errisu'**)*

10 = Fraud Overpayment/Voided Offset.

11 = Nonfraud Recoverable Overpayment/Voided Offset.

12 = Nonfraud Nonrecoverable Overpayment or official action taken to adjust future benefits by decreasing WBA, MBA, KWDA, or RB.

13 = BAM determines payment was too large, although payment "technically" proper due to finality rules.

14 = BAM determines payment was too large except where formal warning rules for unacceptable work search efforts prohibit official action. Payment "technically" proper due to law/rules requiring formal warnings for unacceptable work search efforts.

15 = BAM determines payment was too large, although payment "technically" proper due to rules other than finality or formal warning rules for unacceptable work search efforts.

16 = Overpayment established or WBA, KWDA, entitlement, MBA, or RB decreased which was later "officially" reversed, revised, adjusted, or modified and BAM disagrees with "official" action.

Source: *U.S. Department of Labor. 2013. UI Benefit Accuracy Measurement Operations Guide (3rd Edition). p.A-44-A-45.*

https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2013/UIPL_16_13.pdf.

Type II Error Rate, is measured as the sample weighted proportion of underpayments in the paid claims sample and the denied claims sample.

$$\left(\frac{\#\ Underpayment\ Error\ Cases}{Paid\ Claims\ Sample}\right)+\left(\frac{\#\ Underpayment\ Error\ Cases}{Denied\ Claims\ Sample}\right)+\left(\frac{\#\ Erroneous\ Denial\ Cases}{Denied\ Claims\ Sample}\right)$$

The first element of this measure is the proportion of underpayment errors in the paid claims sample. From the original BAM database, these cases fall into any of the following error codes.

List of Underpayment Error Codes *(Data Element '**ei2-KW Action**' of BAM Paid Claims Accuracy Database **'pca_errisu'**)*

20 = Supplemental Check Issued/Offset applied or increase in WBA, KWDA entitlement, MBA, or RB.

21 = BAM determines payment was too small, although payment "technically" proper due to finality rules.

22 = BAM determines payment was too small, although payment "technically" proper due to rules other than finality.

23 = Supplemental check issued/offset applied which was later "officially" reversed, revised, adjusted, or modified, and BAM disagrees with "official" action.

24 = BAM determines payment was too small, but claimant is not entitled to payment due to collateral issues.

Source: U.S. Department of Labor. 2013. UI Benefit Accuracy Measurement Operations Guide (3rd Edition). p.B-51-B-53.

https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2013/UIPL_16_13.pdf.

The second element of this measure is the proportion of underpayment errors in the denied claims sample. From the original BAM database, these cases fall into any of the following codes for the data element '**action** (Error Issue Action Code)' and the value for the data element '**totamt** (Dollar Amount of Error)' in the database **dca_errisu** is greater than 0.

List of Underpayment Error Codes *(Data Element '**action**' of BAM Denied Claims Accuracy Database '**dca_errisu**')*

30 = Claimant was properly denied, but for wrong or different reason/section of law.

20 = DCA investigation determines that the denial determination was improper or benefit payment was too small and official agency action now finds the claimant to be eligible or entitled to a supplemental check issued/offset applied or increase in WBA, dependents' allowance entitlement, MBA, or remaining balance (RB).

21 = DCA investigation determines denial determination was improper or payment was too small, although technically proper due to finality rules.

22 = DCA investigation determines denial determination was improper or payment was too small, although technically proper due to rules other than finality.

23 = DCA investigation determines denial determination was improper or payment was too small (supplemental check issued/offset applied) which was later officially reversed, revised, adjusted or modified, and BAM disagrees with the official action.

24 = DCA investigation determines that the denial determination was improper but no payment is due to the claimant. (Requires Error Cause code 710 or 720).

Source: U.S. Department of Labor. 2013. UI Benefit Accuracy Measurement Operations Guide (3rd Edition). p.B-51-B-53.

https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2013/UIPL_16_13.pdf.

The last dependent variable in this study, *Relative Type I Program Error Rate*, is computed as the total type I error rate (**t1error_rat**) over the total error rate (**totalerror_rat**). This measure only includes errors that are attributable to state UIP agencies. The numerator is equivalent to the second dependent variable, *Absolute Type I Program Error Rate.* The denominator is equivalent to *Total Program Error Rate.*

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https://oui.doleta.gov/unemploy/bam/2004/bam-facts.asp [*Accessed: May 20, 2024*].

U.S. Department of Labor. 2013. UI Benefit Accuracy Measurement Operations Guide (3rd Edition).

https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2013/UIPL_16_13.pdf

[Accessed: December 12, 2023].

APPENDIX B
FIGURE B1
Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)
[Omit Additional Control Variables]

FIGURE B1A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL B1])

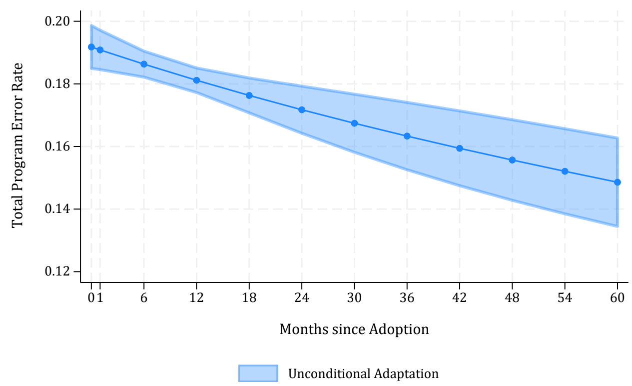


FIGURE B1B
Conditional Adaptation Maiginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL B1])

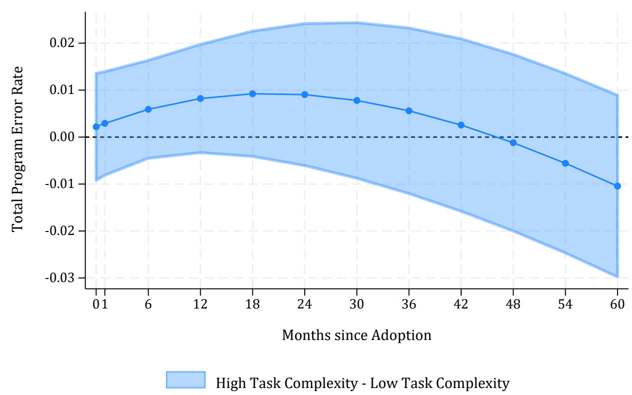


FIGURE B1C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL B1])

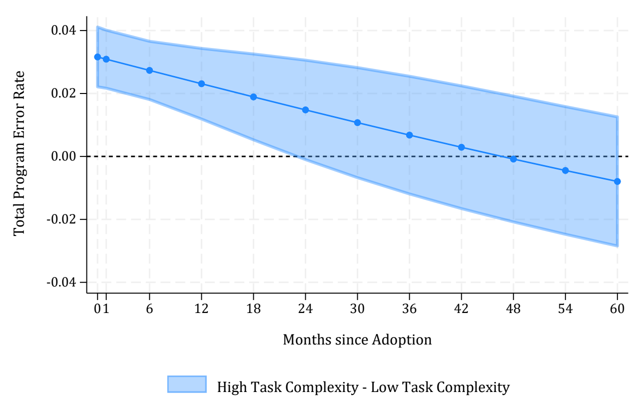


FIGURE B2

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates: Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)

[Omit Additional Control Variables]

FIGURE B2A
Unconditional Adaptation Effect
(Absolute Type I Program Error Rate [MODEL B2])

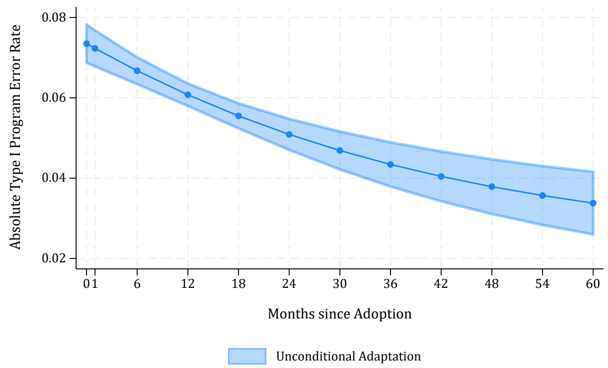


FIGURE B2B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Absolute Type I Program Error Rate [MODEL B2])

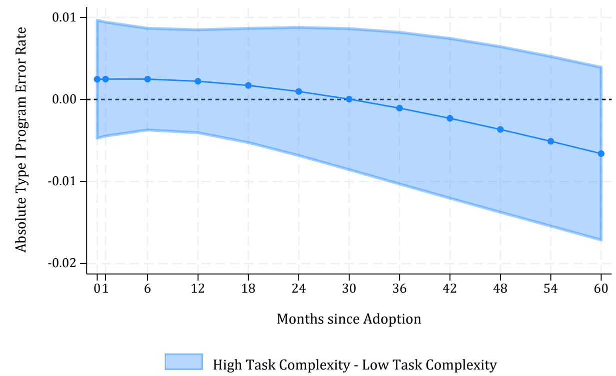


FIGURE B2C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Absolute Type I Program Error Rate [MODEL B2])

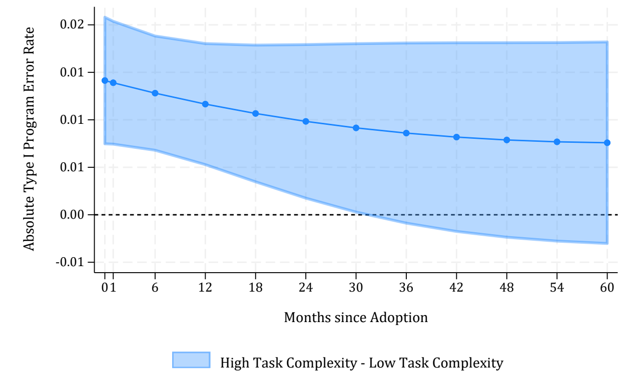


FIGURE B2D
Unconditional Adaptation Effect
(Relative Type I Program Error Rate [MODEL B3])

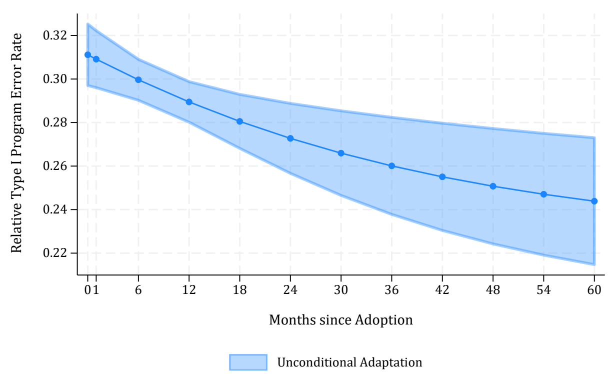


FIGURE B2E
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Relative Type I Program Error Rate [MODEL B3])

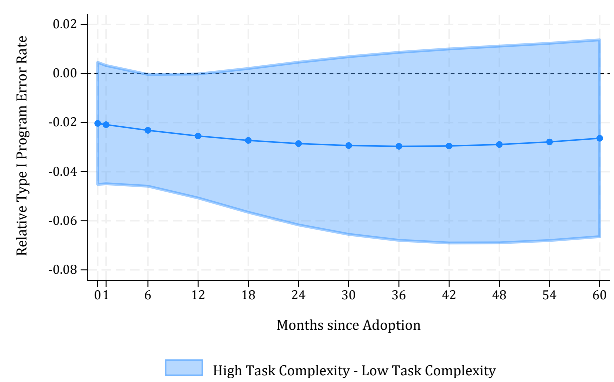
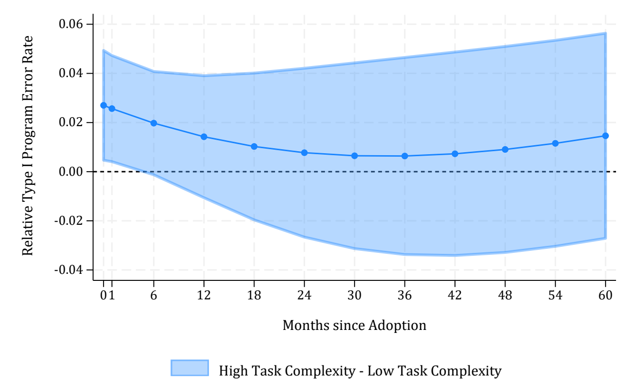


FIGURE B2F
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Relative Type I Program Error Rate [MODEL B3])



APPENDIX C
FIGURE C1
Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)
[Inclusion of Non-IT Adopting States]

FIGURE C1A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL C1])

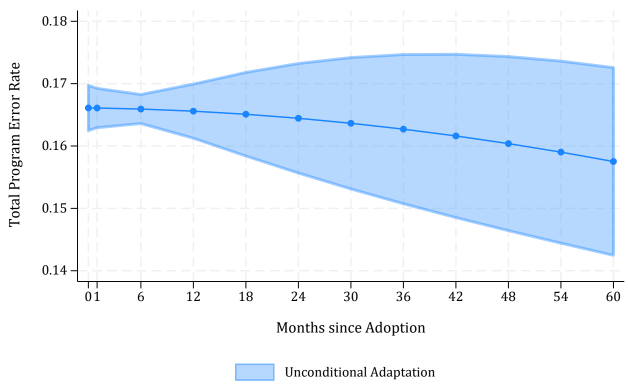


FIGURE C1B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL C1])

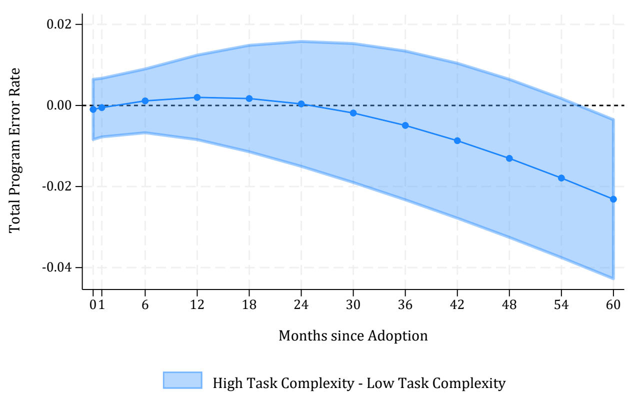


FIGURE C1C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL C1])

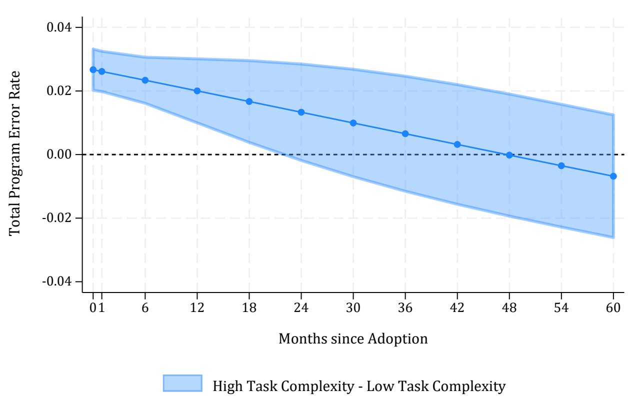


FIGURE C2

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates: Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)

[Inclusion of Non-IT Adopting States]

FIGURE C2A
Unconditional Adaptation Effect
(Absolute Type I Program Error Rate [MODEL C2])

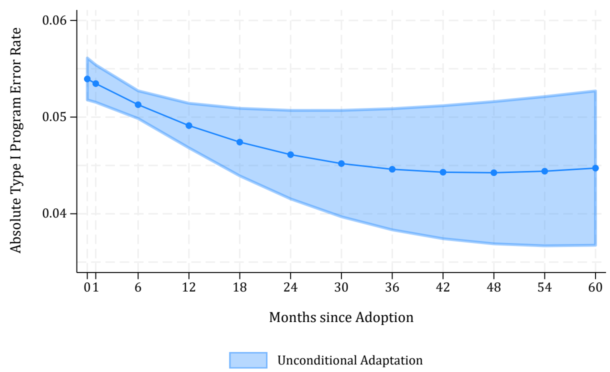


FIGURE C2B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Absolute Type I Program Error Rate [MODEL C2])

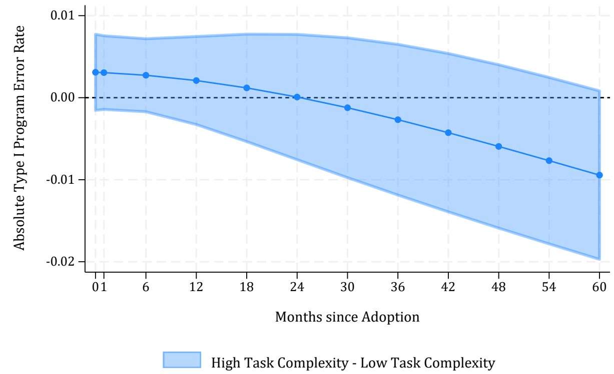


FIGURE C2C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Absolute Type I Program Error Rate [MODEL C2])

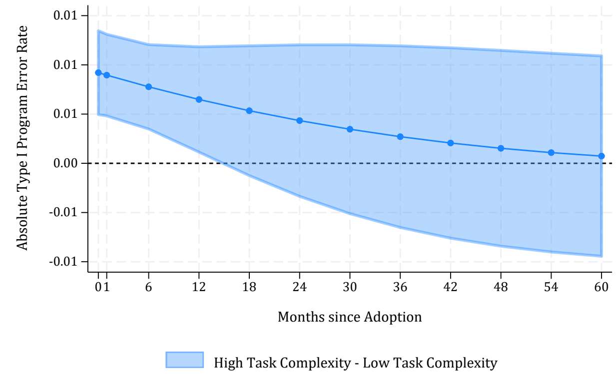


FIGURE C2D
Unconditional Adaptation Effect
(Relative Type I Error Rate [MODEL C3])

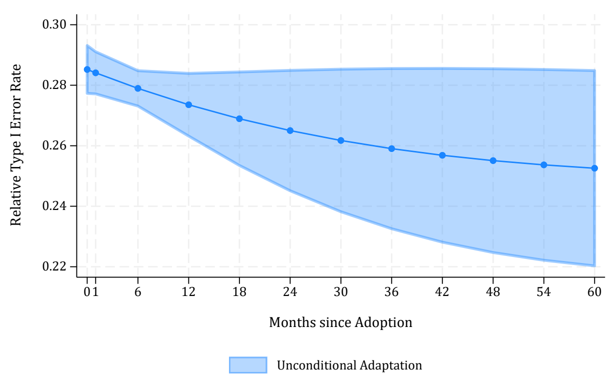


FIGURE C2E
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Relative Type I Error Rate [MODEL C3])

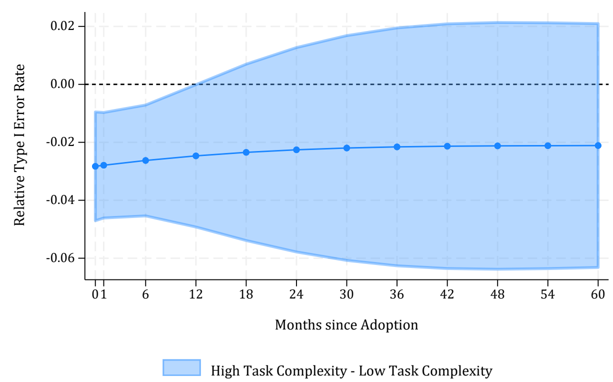
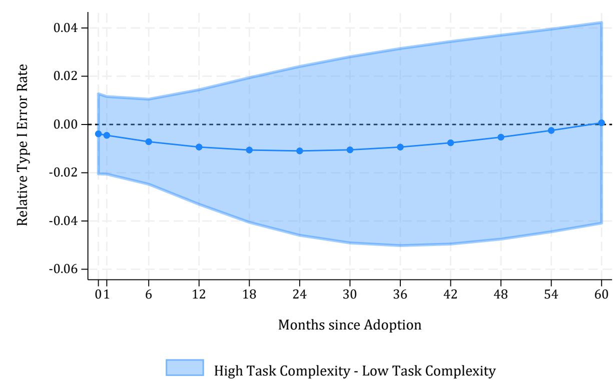


FIGURE C2F
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Relative Type I Error Rate [MODEL C3])



APPENDIX D

FIGURE D1

Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)

[Omit State Panels Involving 2nd IT Modernization Reforms [Nebraska & New Mexico] & 2020-2022 Cases]

FIGURE D1A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL D1])

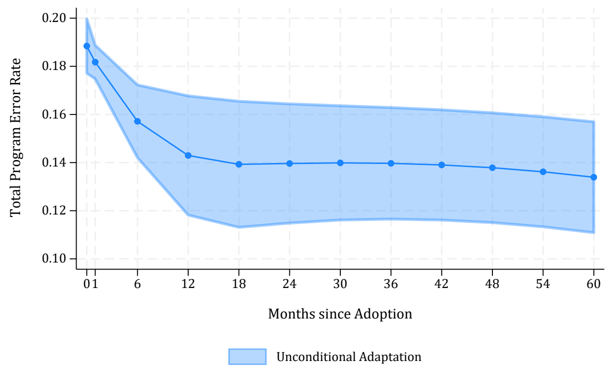


FIGURE D1B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL D1])

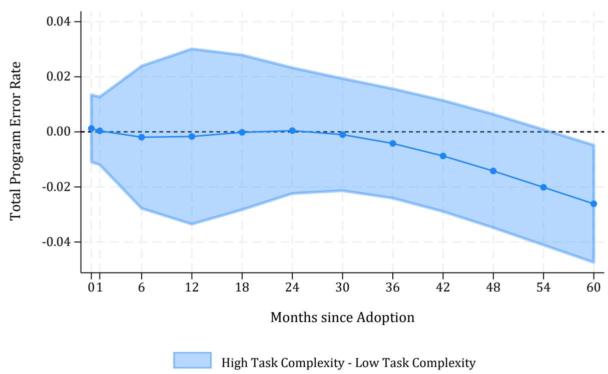


FIGURE D1C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL D1])

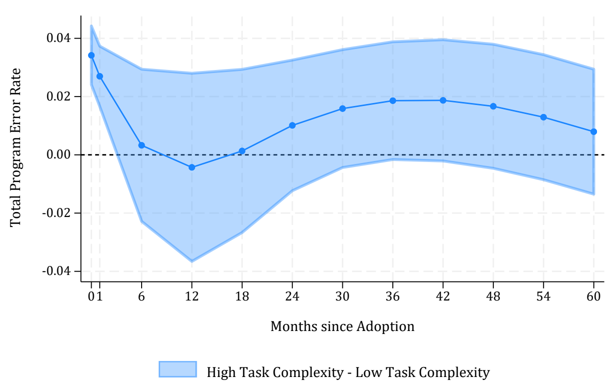


FIGURE D2

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates: Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)

[Omit State Panels Involving 2nd IT Modernization Reforms [Nebraska & New Mexico] & 2020-2022 Cases]

FIGURE D2A
Unconditional Adaptation Effect
(Absolute Type I Program Error Rate [MODEL D2])

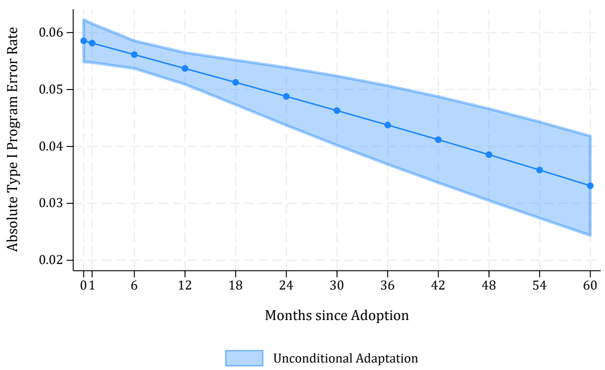


FIGURE D2B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Absolute Type I Program Error Rate [MODEL D2])

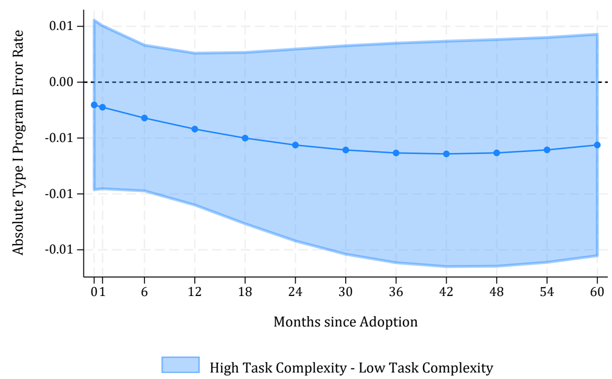


FIGURE D2C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Absolute Type I Program Error Rate [MODEL D2])

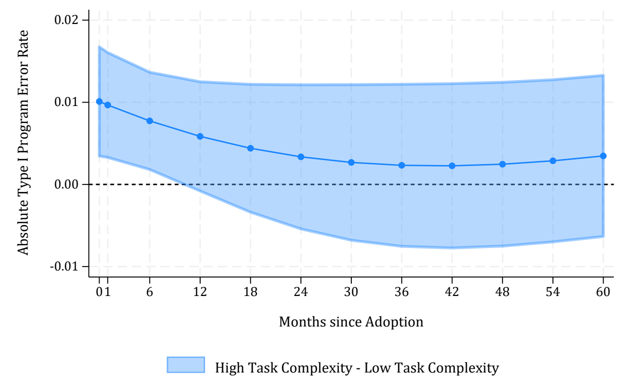


FIGURE D2D
Unconditional Adaptation Effect
(Relative Type I Error Rate [MODEL D3])

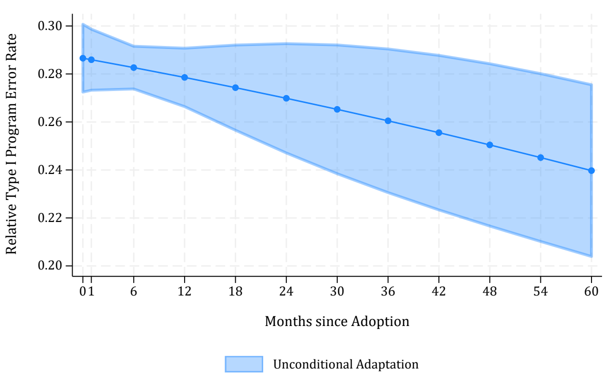


FIGURE D2E
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Relative Type I Program Error Rate [MODEL D3])

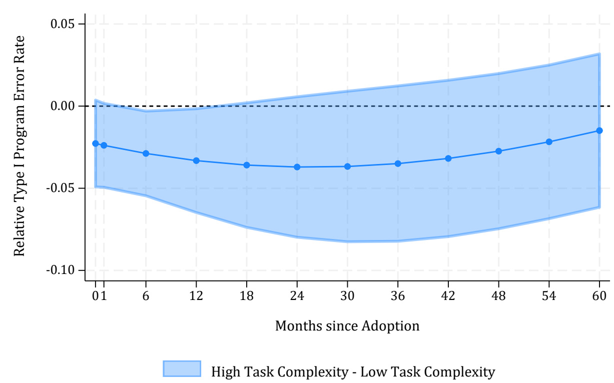
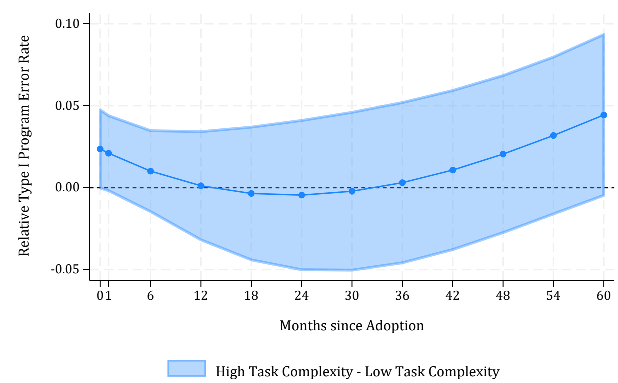


FIGURE D2F
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Relative Type I Program Error Rate [MODEL D3])



APPENDIX E

FIGURE E1

Analyzing Relative Type I Program Error Rates: Disaggregating Type II Errors Resulting from Underpayment Errors, Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4) [In Relation to Underpayment Type II Program Error Rate]

FIGURE E1A
Unconditional Adaptation Effect
(Relative Type I Program Error Rate: Underpayment Type II Program Error Rate)
[MODEL E1]

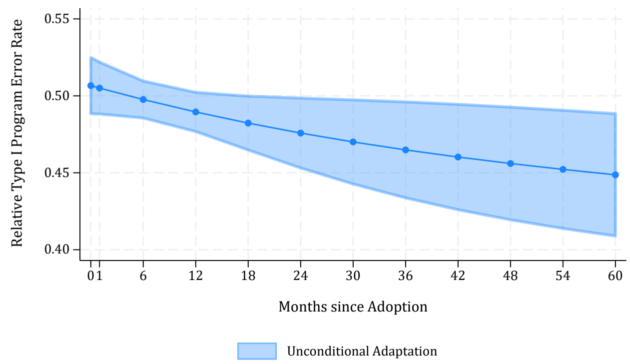


FIGURE E1B
Conditional Adaptation Marginal Effect By Task Complexity: Interstate Claims
(Relative Type I Program Error Rate: Underpayment Type II Program Error Rate)
[MODEL E1]

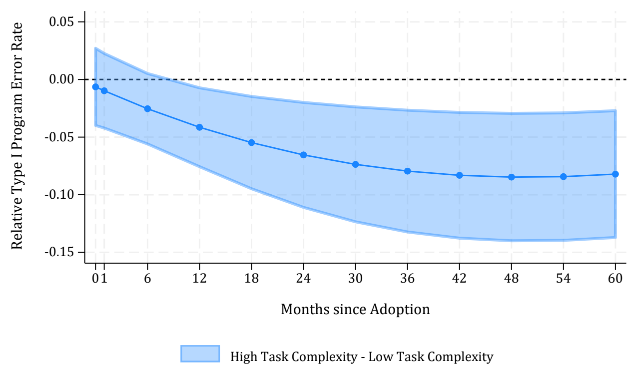
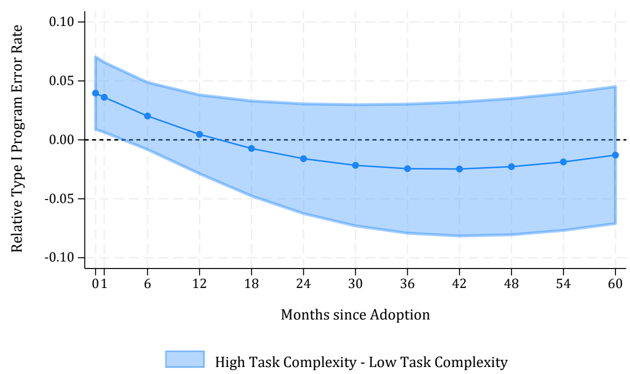


FIGURE E1C
Conditional Adaptation Marginal Effect By Task Complexity: Seeking Different Occupation
(Relative Type I Program Error Rate: Underpayment Type II Program Error Rate)
[MODEL E1]



<u>FIGURE E2</u>

Analyzing Relative Type I Program Error Rates: Disaggregating Type II Errors Resulting from Erroneous Denial Errors, Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4) [In Relation to Erroneous Denial Type II Program Error Rate]

FIGURE E2A
Unconditional Adaptation Effect
(Relative Type I Program Error Rate: Erroneous Denial Type II Program Error Rate)
[MODEL E2]

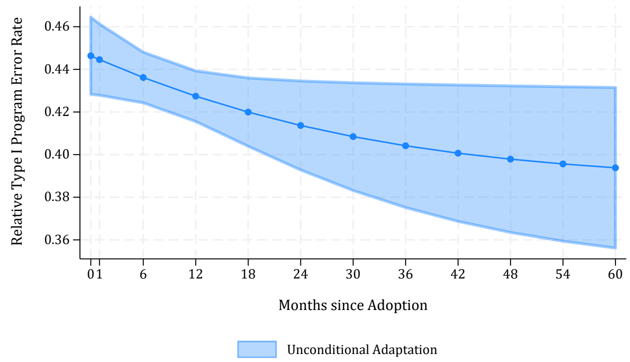


FIGURE E2B
Conditional Adaptation Marginal Effect By Task Complexity: Interstate Claims
(Relative Type I Program Error Rate: Erroneous Denial Type II Program Error Rate)
[MODEL E2]

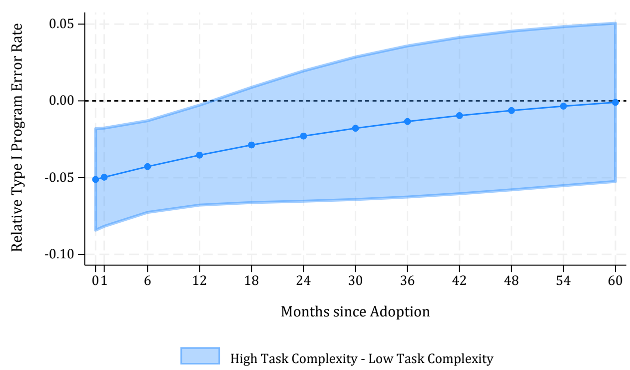
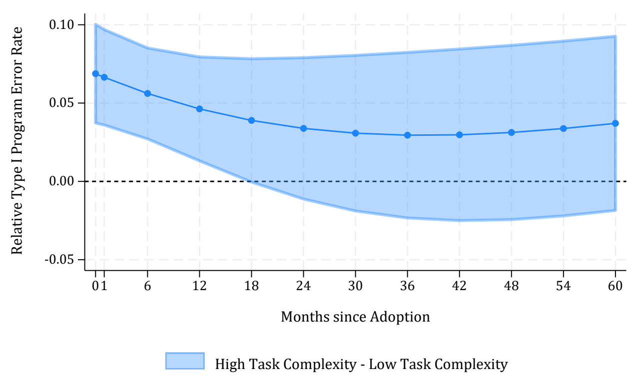


FIGURE E2C
Conditional Adaptation Marginal Effect By Task Complexity: Seeking Different Occupation
(Relative Type I Program Error Rate: Erroneous Denial Type II Program Error Rate)
[MODEL E2]



<u>APPENDIX F</u>
<u>FIGURE F1</u>
Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)

[Placebo Intervention Treatments: IT Modernization Reform Project Start Dates: Exclusion of 'Adoption Treatment' as Control Covariate]

FIGURE F1A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL F1])

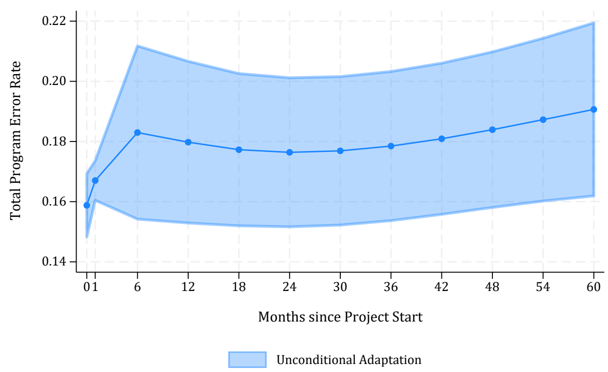


FIGURE F1B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL F1])

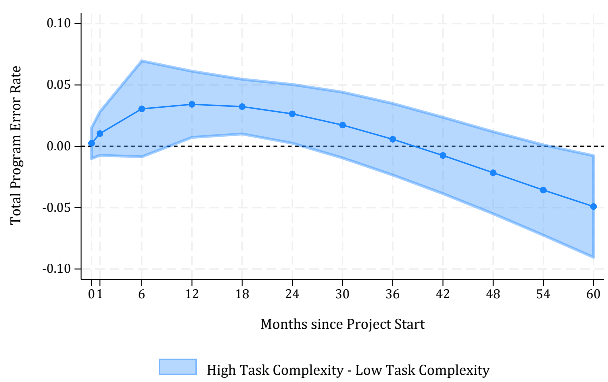


FIGURE F1C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL F1])

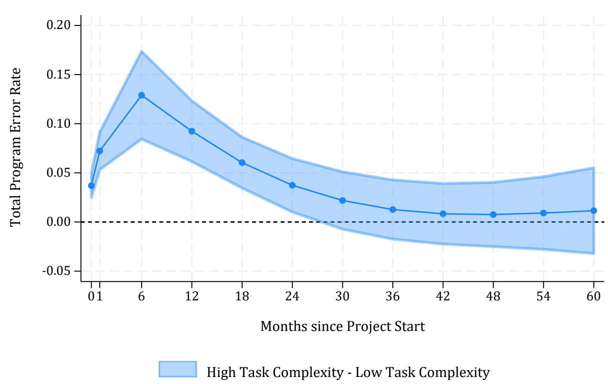
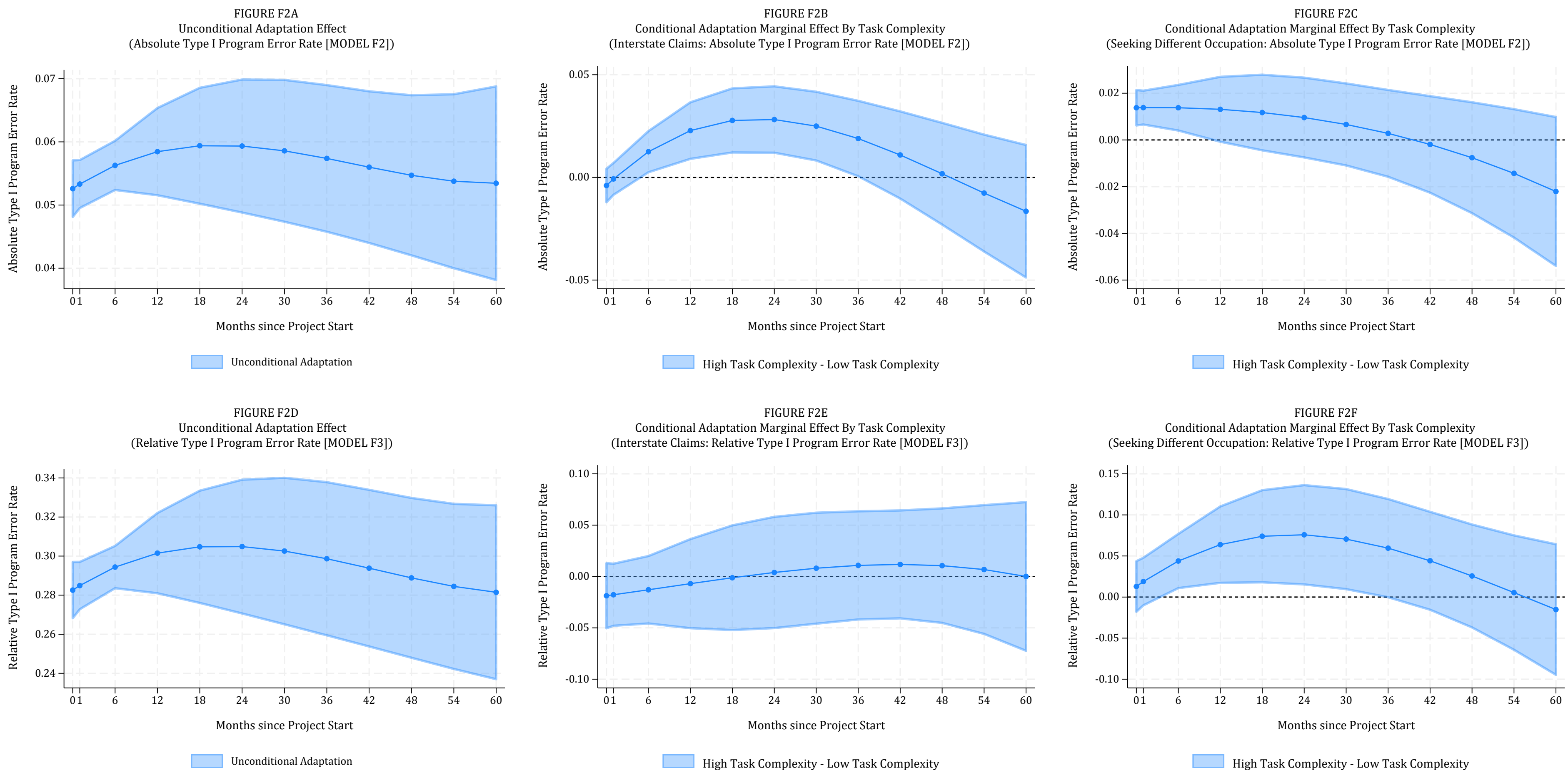


FIGURE F2

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates:
Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)

[Placebo Intervention Treatments: IT Modernization Reform Project Start Dates: Exclusion of 'Adoption Treatment' as Control Covariate]



APPENDIX F

FIGURE F3

Organizational Adaptation Effects from IT Modernization on Total Program Error Rates: Unconditional (H1) and Conditional Adaptation Estimates by Task Complexity (H3)

[Placebo Intervention Treatments: IT Modernization Reform Project Start Dates: Inclusion of 'Adoption Treatment' as Control Covariate]

FIGURE F3A
Unconditional Adaptation Effect
(Total Program Error Rate [MODEL F4])

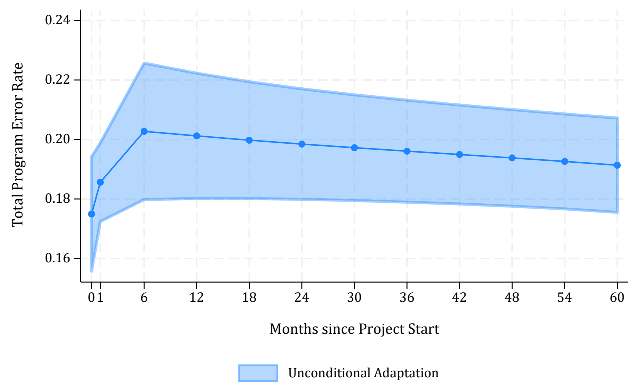


FIGURE F3B
Conditional Adaptation Marginal Effect By Task Complexity
(Interstate Claims: Total Program Error Rate [MODEL F4])

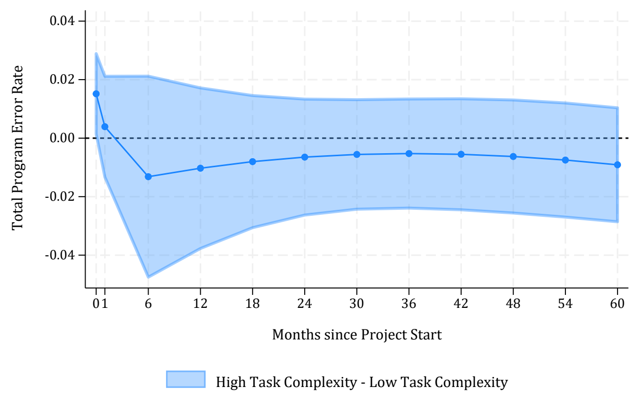


FIGURE F3C
Conditional Adaptation Marginal Effect By Task Complexity
(Seeking Different Occupation: Total Program Error Rate [MODEL F4])

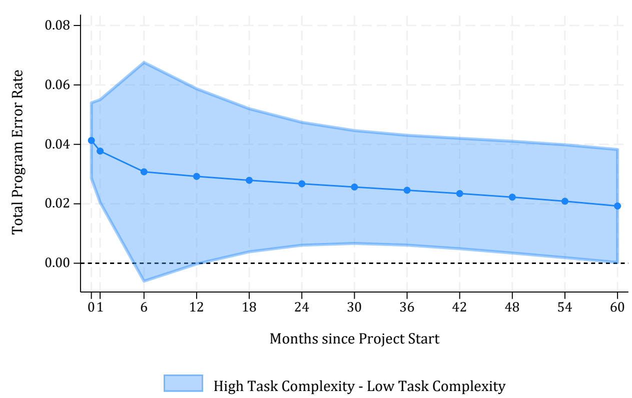


FIGURE F4

Organizational Adaptation Effects from IT Modernization on Type I Program Error Rates: Unconditional (H2) and Conditional Adaptation Estimates by Task Complexity (H4)

[Placebo Intervention Treatments: IT Modernization Reform Project Start Dates: Inclusion of 'Adoption Treatment' as Control Covariate]