AI-tocracy

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Abstract

Can frontier innovation be sustained under autocracy? Recent scholarship has suggested that artificial intelligence technology and autocratic regimes may be mutually reinforcing. We test for such a mutually reinforcing relationship in the context of facial recognition AI in China. To do so, we gather comprehensive data on AI firms and government procurement contracts, as well as on social unrest across China during the last decade. We first show that autocrats benefit from AI: local unrest leads to greater government procurement of facial recognition AI as a new technology of political control, and increased AI procurement indeed suppresses subsequent unrest. We then show that AI innovation benefits from autocrats' suppression of unrest: the contracted AI firms innovate more both for the government and commercial markets, and are more likely to export their products; and non-contracted AI firms do not experience detectable negative spillovers. Taken together, these results suggest the possibility of sustained AI innovation under the Chinese regime: AI innovation entrenches the regime, and the regime's investment in AI for political control stimulates further frontier innovation.

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1 Introduction

Autocratic institutions have long been viewed as fundamentally misaligned with frontier innovation: autocrats' political and economic rents are eroded by technological change and economic growth; and incentives to innovate are stifled by threats and acts of expropriation under autocracy.

Recent scholarship, however, has suggested that artificial intelligence (AI) technology — considered to be the basis for a "fourth industrial revolution" (Schwab, 2017) — may exhibit characteristics that allow an alignment between frontier innovation and autocracy. As a technology of prediction (Agrawal et al., 2019), AI may be particularly effective at enhancing autocrats' social and political control (Zuboff, 2019; Tirole, 2021; Acemoglu, 2021). Furthermore, government purchases of AI may generate broad innovation spillovers, such as those observed among dual-use technologies (Moretti et al., 2019). More specifically, because government data is an input into developing AI prediction algorithms and can be shared across multiple purposes (Beraja et al., 2021), autocracies' collection and processing of data for purposes of political control may directly stimulate AI innovation for the commercial market, far beyond government applications. These arguments imply the possibility of a mutually reinforcing relationship in which governments procure AI to achieve political control, and this procurement stimulates further innovation in the technology.

Empirical evidence supporting such a mutually reinforcing relationship is lacking. As a technology still in its infancy, there exists little systematic evidence on the political deployment of AI, and essentially none on its efficacy in political control. Moreover, while (Beraja et al., 2021) show that government data accessed through procurement contracts is valuable to stimulate commercial innovation among the contract-awarded firms, this does *not* imply aggregate frontier innovation arises from contracts issued explicitly out of political control motives. For example, AI firms selected to provide government services in politically sensitive environments may be differentially specialized in technology (only) for government use; firms' production and service provision for government in such a context may also require significant reallocation of resources that could crowd-out their commercial and broader innovation activities; and contract-awarded firms may impose substantial negative spillovers on peer firms that have not received such contracts due to business stealing or attracting productive inputs such as human capital.

In the context of facial recognition AI in China, we present evidence that frontier innovation and an autocratic regime can indeed be mutually reinforcing. In addition to the economic importance and geopolitical stakes of this context, it is also particularly suitable for studying innovation under autocracy. Maintaining political control is a paramount objective of the ruling Chinese Communist Party (see, among others, Shirk, 2007). All citizens, even China's most successful entrepreneurs, are threatened by an unconstrained autocrat's ability to violate their property rights — and at times civil rights.[1] Moreover, China is among the world's leading producers of commercial AI innovation, and facial recognition is one of the most important fields of AI technology.[2]

To conduct our empirical analyses, we combine several data sources: *(i)* episodes of local political unrest in China from the GDELT project; *(ii)* local public security agencies' procurement of facial recognition AI (and the deployment of complementary surveillance technology) primarily from China's Ministry of Finance; and *(iii)* China's facial recognition AI firms' new software development (registered with the Ministry of Industry and Information Technology), as well as their software export deals (compiled through press releases, news reports, and other sources). Linking datasets *(i)* and *(ii)* allows us to test whether autocracies procure facial recognition AI for purposes of political control, whether facial recognition AI is effective in suppressing unrest, and whether AI procurement is associated with complementary changes in the technology of political control (such as the procurement of surveillance cameras). Then, linking these two datasets to *(iii)* enables us to test the extent to which facial recognition AI innovation benefits from politically motivated procurement — specifically, whether total software development increases, whether software intended for commercial markets (beyond political uses) increases, and whether internationally competitive products emerge.

We begin by examining the first direction in a mutually reinforcing relationship: whether AI technology can effectively enhance autocrats' political control. We first test whether autocrats respond to political unrest by procuring facial recognition AI technology. We find that indeed they do: locations experiencing episodes of political unrest increase their public security procurement of facial recognition AI. This result holds controlling for a range of time-varying local characteristics, including local government fiscal revenue. One might wonder whether the procurement of public security AI was already on a different trend in locations experiencing political unrest (e.g., due to anticipation of subsequent unrest, or because of different rates of economic growth). However, we find quantitatively small increases in AI procurement just prior to episodes of political unrest, and a substantially larger increase in AI procurement during the quarter immediately following episodes of unrest. One might also wonder whether time and space varying

[1] For example, Jack Ma, the founder of Alibaba, was detained for months upon arousing the ire of the Chinese Communist Party. See, for example, from the *Wall Street Journal*, `https://on.wsj.com/3rhtD0l`.

[2] For example, in 2020, computer vision was the second largest field of study in AI by publications on arXiv, accounting for 31.7% of the total publications (Zhang et al., 2021).

shocks are correlated with the occurrence of political unrest and with public security AI procurement. To address this concern, we implement an IV strategy exploiting variation in the occurrence of political unrest arising from local weather conditions, and we find qualitatively and quantitatively similar results. Further evidence of a broad technological upgrade in political control suggests that the increased AI procurement reflects an active choice by public security agencies in response to political unrest, rather than mere "window-dressing." We find that locations experiencing political unrest purchase more high resolution surveillance cameras, which provide the crucial data input for facial recognition technology. Moreover, public security agencies that have procured more facial recognition AI technologies not only reduce their subsequent hiring of police staff, but also shift the composition of the police force towards higher skilled desk jobs that complement the deployment of AI technology.

Local governments' purchases of AI technology for public security purposes in response to the occurrence of political unrest suggest at least a belief in the effectiveness of such technology in curbing future unrest. We next study whether the increased public security AI procurement does indeed enhance autocrats' political control. Precisely because AI is procured endogenously in locations susceptible to political unrest, rather than examining the relationship between AI procurement and subsequent local protests, we examine how past investment in public security AI mitigates the impact of exogenous shocks that tend to instigate political unrest. We find that weather conditions conducive to protests have smaller effects on contemporaneous unrest in prefectures that have accumulated a larger stock of public security AI capacity up to the previous quarter. Conducting a placebo exercise, we find that such a relationship is *not* observed in response to the accumulated non-public security AI capacity, suggesting that our results are driven by the deployment of public security AI *per se*, rather than by differing socioeconomic conditions in politically sensitive contexts. Importantly, our results are not due to the time-varying effects of past protests that are associated with public security AI investment: local experience of past protest is not associated with differential unrest arising from current weather conditions.

Having established that AI *does* strengthen autocrats' political control, we then examine the second direction in a mutually reinforcing relationship: whether politically motivated AI procurement stimulates AI innovation. We define politically motivated AI procurement as purchases by public security agencies in prefectures that experienced above median levels of political unrest in the previous quarter. We then estimate an event study specification, estimating the effects of a firm's first politically motivated contract on AI software production, controlling for firm and time period fixed effects. We find that prior to receipt of a politically motivated contract, firms do not exhibit differential software production, suggesting that selection into such contracts is largely accounted for by the firm fixed effects. Within the first year of contract receipt, firms produce significantly more AI software; by two years post contract, they produce around 10 (48.6%) more software products. Such an increase is observed not just among software intended for government uses, but importantly, also among software intended for broader commercial applications. To address the concern that political unrest is more likely to occur in economically dynamic locations where commercial AI innovation is also greater, we instead identify politically sensitive environments and classify politically motivated procurement contracts using *predicted* political unrest based on weather conditions, and the results are qualitatively unchanged. In other words, plausibly exogenous episodes of political unrest promote commercial AI innovation through increased local public security demand for AI.

An important concern is whether contracts issued in a politically sensitive environment either provide benefits to firms that could account for their increase in innovation activities (e.g., closer government-business ties) or induce differential selection of contract-awarded firms (e.g., greater scrutiny of firms' capacity and potential). To address this concern, we compare the effects of public security contracts issued in this politically sensitive environment — these contracts are most plausibly politically motivated — with the effects of non-public security contracts issued in the same environment. This allows us to isolate the effects of politically motivated contracts beyond the consequences arising from generic contracts issued in a politically sensitive environment. Using a triple-differences empirical strategy, we find that receipt of a politically motivated public security contract is associated with significantly greater innovation of commercial (as well as government) software, relative to the receipt of a contract with a non-public security arm of the government. We find no evidence of differential pre-contract trends in software innovation, supporting a causal interpretation of our findings. To establish the international competitiveness of the new AI software produced following politically motivated contracts, we test whether receipt of such contracts is associated with the firms' greater likelihood to export their products. Indeed, we find a tripling of the likelihood to begin exporting, suggesting that politically motivated contracts have pushed the awarded firms to the technological frontier.

Finally, we investigate whether autocrats' politically motivated AI demands distort the trajectory of innovation, both at the firm level and at the aggregate level. We ask whether, at the firm level, politically motivated public security contracts induce less commercial innovation than similar public security contracts issued in politically neutral environments (namely, when not preceded by local unrest occurrence). We find that the effects of politically motivated public security contracts on commercial AI innovation are not smaller than other, politically neutral, public security contracts (if anything, we find the effects are larger), suggesting that the political motivation does not diminish the impact of procurement contracts on AI firms' commercial innovation. We next consider the possibility that our firm level findings may be offset in aggregate by negative spillovers to other firms, e.g., due to the allocation of resources or business stealing effects. Specifically, we examine AI innovation among firms never receiving procurement contracts that are: *(i)* headquartered in localities that have experienced political unrest; *(ii)* headquartered in localities where AI firms receiving politically motivated contracts are also headquartered; or *(iii)* part of a mother firm with other subsidiaries that have received politically motivated contracts. We find no evidence of negative spillovers in these cases. If anything, we observe positive spillovers to firms not receiving contracts. This suggests that our firm level effects of politically motivated contracts may increase frontier AI innovation in the aggregate, and such aggregate effect may be larger than the total firm level effects that we identify.

Taken together, these results imply that China's autocratic political regime and the rapid innovation in its AI sector are not in conflict, but mutually reinforce each other. We do not interpret our findings as indicating that China's political stability is primarily achieved through AI technology (yet), nor that China's AI innovation is primarily rooted in political repression. Rather, our findings suggest that a component of China's coercive capacity is derived from the application of AI technology, and China's political repression in turn contributes to AI innovation and in part leads to the rise of China as a leading innovator in AI.

More generally, our analysis of the forces that support a mutually reinforcing relationship between autocrats' political repression and frontier innovation in facial recognition AI sheds light on other prominent episodes of frontier innovation under non-democratic regimes. Such episodes — ranging from the development of aerospace technology in the USSR, to chemical engineering innovation in Imperial Germany — are difficult to reconcile with the large literature that highlights forces that limit innovation and growth in non-democratic contexts.[3] These episodes, however, share important features that mir-

[3]The effects of political institutions on economic growth and frontier innovation have been studied by, among others, North and Weingast (1989), Acemoglu and Robinson (2006), Aghion et al. (2007), North et al. (2009), and Acemoglu and Robinson (2012). Autocracies may also exhibit reduced innovation due to corruption and the misallocation of talent (Murphy et al., 1989; Shleifer and Vishny, 2002). The effects of economic growth on political institutions have been studied by Lipset (1959), Barro (1996), and Glaeser et al. (2007) (see Treisman, 2020 for a recent review).

ror China's facial recognition AI sector: first, the non-democratic regimes appear to derive political power from frontier innovation; second, recognizing the political benefits of innovation, the regimes provide financial and institutional support that may be instrumental to technical development. To the extent that these mutually reinforcing forces overcome traditional autocratic frictions, innovation can entrench autocracies and be promoted by them in a sustained manner.[4]

Our work relates to several additional strands of the literature. We contribute to a growing literature on the socioeconomic consequences of AI technology. Over the past several years, many economists have been studying the far-reaching consequences of an emerging AI-led economy. However, much of the literature focuses on the economic consequences of AI: from its impact on the labor market (Acemoglu and Restrepo, 2018, 2019) and how governments should respond to it (Beraja and Zorzi, 2021), to how it reshapes market power and competition (Jones and Tonetti, 2020; Eeckhout and Veldkamp, 2022), to how it changes global trade (Goldfarb and Trefler, 2018), to how it affects socioeconomic inequality (Korinek and Stiglitz, 2017) and economic growth (Aghion et al., 2017; Farboodi and Veldkamp, 2022). Some recent research has considered the social consequences of AI, in particular, discrimination arising from the potential biases in its algorithms (Kleinberg et al., 2018; Cowgill and Tucker, 2020). Our paper provides the first direct evidence on the political consequences of AI technology: it can produce more effective political control, potentially entrenching autocratic government.

Moreover, we contribute to a recent literature that emphasizes the importance of state capacity for development (e.g., Besley and Persson, 2009). The mutually reinforcing relationship we observe between a regime and frontier innovation can also be observed in settings beyond autocracies where the state exercises its fiscal capacity to support frontier technology (e.g., DARPA in the US). We highlight the possibility of sustained innovation arising from an autocrat's exertion of state capacity for political control. Thus, we contribute to a recent literature allowing for the possibility of growth under extractive institutions (e.g., Acemoglu and Robinson, 2020, Dell and Olken, 2020).[5] Beraja et al. (2021) find that Chinese government contracts stimulate AI innovation, but do not determine

[4]One also observes examples of mutually reinforcing relationships between democratic regimes and frontier innovation. One prominent case is the military innovation developed by DARPA in the US, and its well-known commercial innovation consequences (e.g., the internet). We do not argue that innovation *only* supports autocratic regimes; but rather, that such a regime-enhancing effect of technology may be particularly relevant in non-democracies due to their otherwise unfavorable environment for innovation.

[5]In addition to works cited above, a large empirical literature identifies negative effects of extractive institutions on long-run development (e.g., Acemoglu et al., 2002, Nunn, 2008, Dell, 2010, Lowes and Montero, 2020). There has been, however, a small strand of the literature that documents the positive economic consequences of colonial investments, particularly in transportation infrastructure and human capital (e.g., Hullery, 2009, Cagé and Rueda, 2016, Donaldson, 2018, Valencia Caicedo, 2019).

whether such contracts strengthen the autocrats, and whether politically motivated contracts in particular can foster commercial innovation. In this paper, we demonstrate that frontier innovation *can* be sustained in autocracy as a result of their mutually reinforcing relationship. In fact, this implies a political economy trajectory that defies conventional wisdom: the Chinese case suggests a stable equilibrium exhibiting sustained frontier innovation and further entrenched autocracy.[6]

We also add to a large literature on the relationship between technology and political stability. Recent papers find that advances in information and communication technologies, and the diffusion of social media, have supported protest movements and populist parties in a broad range of settings (Campante et al., 2018; Enikolopov et al., 2020; Qin et al., 2020; Guriev et al., 2021). We, on the other hand, contribute to a literature that documents how technological change can *repress* political unrest, thus strengthening autocracies and incumbents more generally. This literature describes the evolution of repressive technology: from Autocracy 1.0 — the state as a monopolist of violence using the threat of brute force to produce compliance out of fear (Olson Jr., 1993); to Autocracy 2.0 — the state as manipulator of information using propaganda and censorship to produce compliance out of persuasion (Cantoni et al., 2017; Roberts, 2018; Chen and Yang, 2019; Guriev and Treisman, 2019); and finally, to Autocracy 3.0 — the state (and its AI) as monitor, predictor, and manipulator of behaviors to to produce compliance using targeted behavioral incentives (Tirole, 2021). To this literature, we provide the first empirical evidence on the systematic deployment of AI as a part of the state's political control apparatus, documenting its procurement alongside complementary technological inputs and its effects on maintaining political stability.[7]

Finally, we contribute to the literature on the political economy of growth in China. While much work emphasizes factors that promote China's growth *despite* its autocratic politics (Lau et al., 2000; Brandt and Rawski, 2008; Song et al., 2011), we join an emerging strand of the literature that highlights China's autocratic institutional features that facilitate growth (Bai et al., 2020; Beraja et al., 2021). Importantly, we demonstrate that China's stimulus of facial recognition AI innovation is not due to marginal improvements in institutional dimensions such as protection of property rights and rule of law, nor to the enhancement of infrastructure or state capacity more generally; but rather, AI innovation is spurred directly by the application of political repression itself.

[6] It is important to note this political economy equilibrium is not inevitable, because the mutually reinforcing relationship may be offset by autocratic distortions (e.g., risks of expropriation).

[7] Our findings of AI technology being deployed in response to political unrest also contribute to a growing literature that studies authoritarian responsiveness to citizens' political grievances (e.g., Tsai, 2007, Chen et al., 2016, Campante et al., 2021).

In what follows, in Section 2, we discuss the characteristics of frontier AI innovation and autocracies that may lead them to be mutually reinforcing. In Section 3, we describe the data sources we use. In Section 4, we present evidence of the effects of AI technology on autocratic political control. In Section 5, we present the evidence on the effects of politically motivated procurement of AI on innovation. Finally, in Section 6, we conclude by discussing the implications of our findings.

2 A mutually reinforcing relationship between frontier AI innovation and autocracy

AI technologies have been argued to possess characteristics that could generate a mutually reinforcing relationship between innovation and autocracy.[8]

AI technologies are fundamentally about prediction, as highlighted by Agrawal et al. (2018). Predictions are extraordinarily valuable for an autocrat trying to maintain social and political control. They can serve to enhance monitoring (e.g., using prediction algorithms to identify and track individuals), to project human behaviors (e.g., identifying individuals who are more likely to engage in political unrest), and to shape behaviors (e.g., providing targeted sticks and carrots, as studied by Zuboff, 2019 and Tirole, 2021). These political applications of AI technology to suppress and prevent political instability thus contribute to the first direction of a mutually reinforcing relationship: autocratic regimes may derive political power from frontier innovation in AI.

At the same time, autocratic governments' procurement of AI technologies for purposes of political control can stimulate AI innovation beyond mere political purposes. This can occur through particular channels related to AI innovation being data-intensive: firms providing AI services to the state may gain access to valuable government data; and to the extent that such government data or algorithms trained with it are shareable within the firm, they can be used to develop AI products for commercial markets (Beraja et al., 2021). Moreover, government procurement may increase private data collection, which can then be shared across firms due to its non-rivalry (Aghion et al., 2017; Jones and Tonetti, 2020). Procurement of AI technologies could also stimulate innovation through traditional "crowding-in" channels, including the production of non-tangible assets (e.g., ideas) and technological spillovers across government and commercial applications, both

[8] While we focus on the AI sector in this paper, mutually reinforcing relationships between autocracy and frontier innovation appear to have been present in other prominent historical episodes. In Appendix A, we describe several such episodes, including the success of scientific innovation in the Soviet Union and the emergence of the Second German Empire as a powerhouse of science, industry, and innovation.

within a firm and between firms.[9] Public procurement also provides resources to firms that may allow them to cover fixed costs of innovation and overcome financial constraints. These economic consequences of government procurement of AI technology (in particular, by an autocrat) thus contribute to the second direction of a mutually reinforcing relationship: autocratic regimes' demand for AI technology for purposes of political control may stimulate frontier innovation through data provision, as well as financial and institutional support.

When such a mutually reinforcing relationship is sufficiently strong to overcome distortions in autocracies that discourage innovation (e.g., risk of expropriation), it could support an equilibrium — "AI-tocracy" — where an autocratic regime is entrenched, and frontier AI innovation is sustained.[10] It does so by generating a perpetuating cycle in which autocrats are strengthened by AI innovation, and their procurement of this innovation stimulates further innovation, which in turn further strengthens the autocrats.

3 Empirical context and data

We test for the two directions of a mutually reinforcing relationship between autocracy and frontier innovation in the context of facial recognition AI technology in China.

To test whether frontier AI innovation enhances autocratic political control (the first direction of the mutually reinforcing relationship), we examine: *(i)* whether AI procurement is motivated by the regime's desire for political control, and *(ii)* whether procurement of AI technology out of political motivation indeed enhances the regime's political control by reducing unrest.

The Chinese regime is particularly concerned with protests and unrest (Shirk, 2007; King et al., 2013). Thus, consider local government officials' response to an episode of local political unrest. Anticipating that such unrest may persist into subsequent periods — either due to socioeconomic shocks that are serially correlated or because protest participation itself is path dependent (Madestam et al., 2013; Bursztyn et al., 2021) — the local officials may procure facial recognition AI technology and upgrade their political control technology. Such technology could allow the government to preemptively identify, crack down on, and deter the participants in future unrest, thus mitigating the effect of future

[9] These channels have been shown to be important in the context of space exploration (Alic et al., 1992; Azoulay et al., 2018), the internet (Greenstein, 2015), as well as military technology (Moretti et al., 2019; Gross and Sampat, 2020).

[10] In fact, autocrats' sustained demand for AI technology for purposes of political control may also enhance their ability to commit to protect AI innovators' property rights, thus reducing the risk of expropriation.

shocks on generating local unrest.

To test the second direction of the mutually reinforcing relationship, we examine whether politically motivated procurement of AI technology stimulates further frontier AI innovation of the contract awarded firms. Government procurement could provide these firms with valuable inputs such as access to rich public security data and revenue streams, which may allow the AI firms to develop more and newer AI products. To the extent that these inputs may be shared across multiple purposes, the AI firms could increase their innovation activities in the commercial sector above and beyond those developed for government purposes, thus moving out the innovation frontier. We close by considering the effects of politically motivated contracts on firms not awarded these contracts, thus gauging the potential aggregate innovation consequences.

To conduct our empirical analyses, we combine data on: *(i)* episodes of local political unrest in China; *(ii)* local governments' procurement of facial recognition AI technology and complementary technology for political control; and *(iii)* facial recognition AI firms' software innovation and product export activities. We describe, in addition, auxiliary data sources used for various empirical exercises in Appendix B.

3.1 Political unrest

We collect data on political unrest from the Global Database of Events, Language, and Tone (GDELT) Project. The GDELT project records instances of events based on articles from a global, comprehensive set of news feeds.[11] We restrict our analysis to events taking place in China between 2014 to 2020.[12] In sum, we find 9,267 events indicating political unrest, corresponding to three broad categories: protests, demands, and threats.[13] Figure 1, Panel A, presents the spatial distribution of the political unrest that occurred during the period of 2014 to 2020 in prefectures with AI contracts that we study; and

[11]Text analysis and machine learning methods are applied to the contents of these articles to identify salient characteristics, such as event location (which we geocode at the prefecture level), date of the event, and the nature of these events. See `https://www.gdeltproject.org` for a detailed description of the GDELT Project and its methodology.

[12]The GDELT Project greatly expanded their scope of sources and text analysis capabilities in 2014, making coverage before 2014 less complete and reliable. From 2014 to 2020, there are over one hundred news sources that provide coverage on China. When multiple news sources cover the same event, GDELT records only one event.

[13]Each event is classified under the Conflict and Mediation Events Observations (CAMEO) event and actor codebook, in which protests (e.g., demonstrations, hunger strikes for leadership change), demands (e.g. demands for material aid, leadership change, or policy change), and threats (e.g., threats to boycott, political dissent) are three of twenty top-level "verbs" that an event can be classified under, with the latter being relatively less politically threatening. We exclude a small number of events that occur at a national or international level. We are able to cross-check the protest data against similar event counts from alternative sources, such as Radio Free Asia (Qin et al., 2020), and find very similar levels.

Table 1, Panel A, presents basic summary statistics of these political unrest events.

Given the state control of Chinese media sources, it is important to consider the possible impact of censorship on the quality of the GDELT data. We believe that the GDELT data is well-suited for our purposes for several reasons. First, the local unrest that we focus on has generally *not* been targeted for censorship by the Chinese authorities (Qin et al., 2017); some have even argued that media reporting on local unrest is particularly helpful to resolve the information asymmetry between the central and local government (Lorentzen, 2013). Moreover, the GDELT data includes a range of unrest events that differ in their political sensitivity, allowing us to examine whether the patterns we observe vary by political sensitivity.

Local weather conditions used to construct instruments for political unrest We use historical weather data originally collected by the World Meteorological Organization (WMO) and hosted by the National Oceanic and Atmospheric Administration (NOAA). Data is reported at the weather station-day level. These weather stations provide a wide variety of data at the daily level, including mean temperature, amount of precipitation, presence of fog or rain or hail or thunder, maximum windspeed recorded, and visibility.[14] Importantly, we use all 18 weather variables that are consistently available throughout the globe during our sampling period. We assign data to prefectures using the closest weather station to the given prefecture. For the 344 prefectures in our dataset, this results in 260 unique weather stations whose data we use.

3.2 Procurement of AI and the technology of political control

In order to observe the Chinese government's demand for AI technology, we extract information on 2,997,105 procurement contracts issued by all levels of the Chinese government between 2013 and 2019 from the Chinese Government Procurement Database, maintained by China's Ministry of Finance.[15] The contract database contains information on the good or service procured, the date of the contract, the monetary size of the contract, the winning bid, as well as, for a subset of the contracts, information on bids that did not win the contract.

[14]Other weather variables are: mean dew point, mean sea level pressure, mean station pressure, mean wind speed, maximum wind gust, maximum temperature, minimum temperature, snow depth, and presence of tornadoes or funnel clouds. This weather data ranges from 2012 to 2020. There are a small number of observations for which weather data is missing (less than 1% of the total). For these, we impute data from the geographically nearest weather station, or in the one instance when all stations are missing data on a given day, we take data from the following day and the same station instead.

[15]See Appendix Figure A.1 for an example contract.

To narrow our focus on the subset of contracts that procure facial recognition AI technology such as data processing services or platform solutions, we match the contracts with a list of facial recognition AI firms. We identify (close to) all active firms based in China producing facial recognition AI using information from *Tianyancha*, a comprehensive database on Chinese firms licensed by China's central bank.[16] We extract firms that are categorized as facial recognition AI producers by the database, and we validate the categorization by manually coding firms based on their descriptions and product lists. We collect an array of firm level characteristics such as founding year, capitalization, major external financing sources, as well as subsidiary and mother firm information. Overall, we identify 7,837 Chinese facial recognition AI firms.[17]

Our empirical exercises in particular concern the AI procurement contracts awarded by public security agencies of the Chinese government.[18] As an example from our dataset, consider a contract signed between an AI firm and a municipal police department in Heilongjiang Province to "increase the capacity of its identity information collection system" on August 29th, 2018. The contract specifies that the AI firm shall provide a facial recognition system that should cover at least *30 million* individuals, suggesting the large scale of data collection and processing that are required. In total, we identify 28,023 public security related procurement contracts on AI technology.[19] They include the following four types of public security contracts from the Chinese Government Procurement Database: *(i)* all contracts for China's flagship surveillance/monitoring projects — *Skynet Project*, *Peaceful City Project*, and *Bright Transparency Project*; *(ii)* all contracts with local police departments; *(iii)* all contracts with the border control and national security units; and, *(iv)* all contracts with the administrative units for domestic security and stability maintenance, the government's political and legal affairs commission, and various "smart city" and digital urban management units of the government. Importantly, each of these contracts is linked to a specific prefectural government buyer, and for the baseline analysis,

[16]A primary source of firms' information compiled by Tianyancha is the National Enterprise Credit Information Publicity System, maintained by China's State Administration for Industry and Commerce. See Appendix Figure A.2 for an example entry. We complement the *Tianyancha* database with information from *Pitchbook*, a database owned by Morningstar on firms and private capital markets around the world. See Appendix Figure A.3 for an example entry.

[17]These firms fall into 3 categories: *(i)* firms specialized in facial recognition AI (e.g., Yitu); *(ii)* hardware firms that devote substantial resources to develop AI software (e.g., Hik-Vision); and *(iii)* a small number of distinct AI units within large tech conglomerates (e.g., Baidu AI).

[18]Parts of our empirical strategy compare public security procurement contracts of AI to those awarded by non-public security units in the public sector, such as (public) banks, hospitals, and schools. There are a total of 6,557 non-public security related procurement contracts of AI technology.

[19]We present the cumulative number of AI procurement contracts in Appendix Figure A.4 (top panel), as well as the flow of new contracts signed in each month (bottom panel). Both public security and non-public security AI contracts have steadily increased since 2013.

we exclude those signed with the central or provincial government. Many firms receive multiple public security contracts; overall, 1,095 facial recognition AI firms in our dataset receive at least one contract. Figure 1, Panel B, presents the spatial distribution of the facial recognition AI contracts issued by public security units of the prefectural government.[20]

In addition to the public security agencies' procurement of AI technology, we also collect information on a key complementary technology for political control: high resolution surveillance cameras procured by the same agencies. These cameras, once deployed in the public space, could provide richer data that would make the facial recognition AI platform more effective and accurate, and may also deter violations of public security and political stability. Table 1, Panel B, presents basic summary statistics of the facial recognition AI procurement contracts issued by public security and non-public security agencies, as well as the procurement of surveillance cameras.

3.3 Innovation of AI firms

Product innovation: AI software development We collect all software registration records for our facial recognition AI firms from China's Ministry of Industry and Information Technology, with which Chinese firms are required to register new software releases and major upgrades. We are able to validate our measure of software releases (using a single large firm), by cross-checking our data against the IPO Prospectus of MegVii, the world's first facial recognition AI company to file for an IPO.[21] We find that our records' coverage is comprehensive (at least in the case of MegVii): MegVii's IPO Prospectus contains 103 software releases, all of which are included in our dataset.

The count of new software releases (and major upgrades) represents *product innovation*.[22] Reflecting the economic value of such innovation, we observe that facial recognition AI firms that develop more software have significantly and substantially higher market capitalization (see Appendix Figure A.6).

We use a Recurrent Neural Network (RNN) model with tensorflow — a frontier method for analyzing text using machine learning — to categorize software products according to their intended customers and (independently) by their function. Our categorization by

[20]Some public security AI contracts are issued at the provincial level: for example, almost 40% of the public security AI contracts in Xinjiang are issued by the provincial government. Appendix Figure A.5 plots the spatial distribution of public security AI contracts issued by either provincial or prefectural governments.

[21]Source: Hong Kong Stock Exchange, `https://go.aws/37GbAZG`.

[22]The National Science Foundation defines product innovation as "the market introduction of a new or significantly improved good or service with respect to its capabilities, user-friendliness, components, or subsystems" in its Business Enterprise Research and Development Survey (see `https://www.nsf.gov/statistics/srvyberd`). See also Bloom et al. (2020).

customer distinguishes between software products developed for the government (e.g., "smart city — real time monitoring system on main traffic routes") and software products developed for commercial applications (e.g., "visual recognition system for smart retail"). We allow for a residual category of general application software whose description does not clearly specify the intended user (e.g., "a synchronization method for multi-view cameras based on FPGA chips"). By coding as "commercial" only those products that are specifically linked to commercial applications, and excluding products with ambiguous use, we aim to be conservative in our measure of commercial software products.

Our categorization by function first identifies software products that are directly related to AI (e.g., "a method for pedestrian counting at crossroads based on multi-view cameras system in complicated situations"). Within the category of AI software, we also separately identify a subcategory of software that involve components related to surveillance (e.g., "tool that allows parents to locate and track lost children").

To implement the two dimensions of categorization using the RNN model, we manually label 13,000 software products to produce a training corpus. We then use word-embedding to convert sentences in the software descriptions into vectors based on word frequencies, where we use words from the full dataset as the dictionary. We use a Long Short-Term Memory (LSTM) algorithm, configured with 2 layers of 32 nodes. We use 90% of the data for algorithm training, while 10% is retained for validation. We run 10,000 training cycles for gradient descent on the accuracy loss function. The categorizations perform well in general: we are able to achieve 72% median accuracy in categorizing software customer and 98% median accuracy in categorizing software function as AI or data-complementary in the validation data. Appendix Figure A.7 shows the summary statistics of the categorization output by customers and by function; and, Appendix Figure A.8 presents the confusion matrix (Type-I and Type-II errors) of the predictions relative to categorization done by humans.[23] Table 1, Panel C.1, presents basic summary statistics of the software innovation of all AI firms (regardless of whether they have received procurement contracts), and Panel C.2 presents the cumulative AI software production prior to firms' receipts of their first public security procurement contracts.

Frontier technology: firms' AI software exports We construct a database of global AI trade deals using the bibliography of the Carnegie Endowment for International Peace's

[23]Appendix Table A.1 presents the top words (in terms of frequency) used for the categorization. Appendix Figure A.9 presents the density plots of the algorithm's category predictions. The algorithm is very accurate in categorizing software for government purposes. The algorithm is relatively conservative in categorizing software products for commercial customers, and relatively aggressive in categorizing them as general purpose. In setting our categorization threshold for commercial software we again aim to be conservative in our measure of commercial software products.

report *The Global Expansion of AI Surveillance* (Feldstein, 2019). This bibliography focuses on international procurement of AI surveillance technology by governments, containing 1,300 citations spanning 75 countries.[24] Examples of such deals include: "Safe City Service Brings the Future to Laos: Huawei case studies" (China exporting to Laos in 2015), "Bosch equips Hong Kong-Zhuhai-Macao Bridge with customized security solutions" (Germany exporting to China in 2018), and "Digital Intelligence is Helping Brazil's Federal Police Seize Millions in Assets to Bring Down Drug-Smuggling Kingpins" (Israel exporting to Brazil in 2020).

We then match each trade deal to the Chinese AI firms, allowing us to identify the date from which the firms begin to export their AI software products. For each Chinese AI firm, we additionally search through their press releases and news reports covering them to expand our database of AI trade deals. Among the 7,837 Chinese facial recognition AI firms we study, we identify a total of 176 export deals.

4 The role of AI in autocrats' political control

4.1 The effect of political unrest on AI procurement and the technology of political control

Our empirical analyses begin by examining whether AI technology can effectively entrench autocrats. Specifically, we first test whether local public security agencies (e.g., police forces) respond to episodes of local political unrest by procuring more facial recognition AI in the following quarter. The time lag reflects the administrative procedure and time needed to initiate and issue a contract in response to an event. We estimate panel models that control for locality and time period fixed effects, both using OLS and implementing an IV specification that exploits differences in unrest occurrence due to local weather conditions.

We first describe the panel OLS strategy, where we estimate the following model:

$$AI_{i,t+1} = \beta Unrest_{it} + \alpha_t + \gamma_i + \delta_t X_i + \epsilon_{it}, \tag{1}$$

where the explanatory variable of interest is $Unrest_{i,t}$, the local political unrest in prefecture i in quarter t, and $AI_{i,t+1}$ is the public security facial recognition AI procurement per capita of prefecture i in the subsequent quarter. We control for time period and prefecture fixed effects, as well as different combinations of time-varying effects of prefecture

[24] The original bibliography is accessible at `https://www.zotero.org/groups/2347403/global_ai_surveillance/library`.

socioeconomic characteristics. Standard errors are clustered at the prefecture level.

We present the results in Table 2, Panel A. To account for changing local economic and political conditions that may be related to both unrest occurrence and facial recognition AI procurement, we control for the prefecture GDP (measured yearly) interacted with a full set of (quarterly) time fixed effects (column 1), the prefecture's log population interacted with a full set of time fixed effects (column 2), the prefectural government's annual fiscal revenue interacted with a full set of time fixed effects (column 3), or all of these controls (column 4). One can see that across specifications, political unrest in a prefecture in one quarter is followed by a significantly greater amount of AI procurement in the following quarter.[25] The results remain qualitatively and quantitatively very similar throughout. The coefficients imply that a one standard deviation increase in local unrest is associated with around 0.20 standard deviation increase in AI procurement. Appendix Table A.2 shows results on political unrest in the separate subcategories of protests, public demands, and threats, with results remaining qualitatively the same. To the extent that reporting of these event types is subject to different degrees of censorship (e.g., due to differences in political sensitivity), these qualitatively similar patterns suggest that differential censorship of local unrest is unlikely to explain the baseline result.

We next examine whether AI procurement may already have been increasing in locations with political unrest *prior* to the unrest itself. We thus estimate a modified version of the baseline model, but additionally estimating the effects of unrest on AI procurement in periods from $t-2$ to $t+3$. Figure 2 plots the estimated coefficient on unrest for each lead and lagged period. As one can see, upcoming political unrest is associated with only slightly higher levels of AI procurement. The association between unrest and procurement is substantially larger one quarter after the unrest occurrence, and such association fades in subsequent quarters. This pattern suggests that AI procurement primarily was in response to, and not in anticipation of, unrest.

As an alternative empirical strategy, we estimate the same panel model with locality and time fixed effects, but now exploiting variation in unrest occurrence arising from daily weather conditions (similar in spirit to Madestam et al., 2013 and Larreboure and Gonzalez, 2021). Government officials may respond to occurrences of unrest even when they arise out of idiosyncratic weather shocks. This may be because officials are unable to distinguish between root causes of unrest, or because it is important to respond to any

[25]Our interpretation of AI procurement as a government response to political unrest suggests that firms receiving public security contracts issued following periods of political unrest should produce AI software for the government oriented towards surveillance. Indeed, we find a significant increase in the production of AI software intended for the government with surveillance functions (see Appendix Figure A.11 for details).

occurrence given the possible path dependence of unrest.

To implement an empirical strategy that instruments unrest occurrence using local weather conditions in our setting requires overcoming three challenges. The first challenge is high-dimensionality: in a country as vast as China, one must consider a wide range of potentially relevant and interacting weather conditions. This makes identifying a strong instrument more difficult, and also increases the researchers' degree of freedom and risk of finding false positives. The second challenge is the need to consider both the extensive and intensive margins of political unrest. Over a relatively long period of time, there are many days in which no unrest takes place (presumably because of the absence of mobilized political demands on those days), implying no elasticity between weather conditions and unrest occurrence. On certain days, unrest occurs across multiple prefectures, and local weather conditions plausibly would influence the likelihood of unrest occurrence in a specific location. A final challenge is the need to aggregate unrest occurrence to match the time frame over which AI procurement decisions are made (several months, which we operationalize as quarterly observations).

To address these challenges, we begin with the complete set of 18 weather variables consistently collected across weather stations in China. Reflecting the importance of weather interactions, we allow each variable to interact with each of the others. Reflecting the daily variation in the potential for (any) local unrest, we allow the full set of weather variables to have heterogeneous effects on a prefecture's unrest occurrence depending on whether unrest occurs in at least one other prefecture on a given day. To identify a first stage while reducing the role of researcher discretion, we implement a LASSO regression to select predictors of unrest events among these weather variables, an indicator of unrest occurrence across China, and their interactions. Finally, we aggregate our first stage to the quarterly level and calculate the standard errors using the cross-fit partialing-out LASSO IV algorithm (Chernozhukov et al., 2018).[26]

In Table 2, Panel B, we present the estimated effect of unrest on AI procurement, now instrumenting for unrest using the LASSO IV.[27] We find that political unrest arising from local weather variation leads to significantly greater public security AI procurement in the subsequent quarter, and this effect is robust to controlling for a variety of time-varying effects of local socioeconomic conditions. The IV analysis corroborates the OLS finding to provide further evidence that the relationship between unrest and subsequent AI pro-

[26] Aggregating unrest events to the quarterly level matches the timing of procurement, and also addresses concerns about intertemporal substitution of unrest events within a narrow window of time.

[27] In Appendix Table A.3, we present the weights assigned by LASSO to each of the selected weather predictors. The top 3 variables that LASSO selects are: Thunder X unrest elsewhere, Thunder X visibility, and Precipitation X pressure X unrest elsewhere.

curement is casual. As shown in Figure 3, we estimate very similar effects of unrest on AI procurement if we instead: *(i)* use a parsimonious set of weather conditions as first stage predictors (rain, thunder, and wind speed); *(ii)* measure the potential for local unrest using political unrest in China over a week rather than on the same day in order to reduce measurement error in the first stage; and *(iii)* implement alternative estimation procedures using Limited-Information Maximum Likelihood (LIML) and Jackknife IV Estimators (JIVE).[28]

Upgraded technology of political control Our evidence above indicates a strong effect of political unrest on public security AI procurement. We next provide further evidence that such procurement reflects an active decision by public security agencies to upgrade their technology of political control. Specifically, we examine whether these agencies make costly investments that could complement and enhance the efficacy of AI technology.

First, one would also expect that the local government should invest in key hardware that complements facial recognition AI: high resolution surveillance cameras, which provide the fundamental video data processed by the AI algorithm. In Table 3, Panel A, we replicate the exercise in Table 2, but instead examining the local public security procurement of surveillance cameras. We find that following the occurrence of political unrest, the local public security units also increase their procurement of high resolution surveillance cameras. The timing of surveillance cameras procurement matches that of the AI procurement, with a substantial increase in the quarter following the unrest occurrence (see Appendix Figure A.12). Examining the locality's decision to jointly procure AI technologies and surveillance cameras, measured as the product of the two, we find a similar (but larger in magnitude) effect, reflecting public security agencies' decision to invest in both following unrest occurrence (see Table 3, Panel B, and Appendix Figure A.13).

Second, one may expect changes in the local public security agencies' personnel arrangements as they increasingly deploy AI technologies (Acemoglu et al., 2022). In particular, it has been argued by Acemoglu and Restrepo (2019) and Agrawal et al. (2019) that AI technology is one that is often labor-saving and likely to be skill-biased. In the context of public security agencies, AI technology may substitute for patrol officers while still necessitating officers to analyze and act on the AI output. Consistent with these predictions, we find that local police hiring is significantly lower one year after the corresponding po-

[28]One may also be concerned about the robustness of the cross-fit partial-out LASSO algorithm, given the randomness in the process of drawing folds for cross-fitting. Across all specifications, we set the seed to 1(only positive integers are available). Results using the first 100 seeds are also shown under Appendix Figure A.10. The 50th percentile coefficient estimate is 0.241.

lice department procures AI technology, and the share of desk (as opposed to patrol) police significantly increases among the new hires (see Appendix Table A.4 for details). This suggests that the local public security agencies adjust their personnel composition alongside the deployment of facial recognition AI.

Taken together, these results suggest that the autocrat and its public security arms view AI technology as potentially useful and actively procure AI as an advanced method for political control. Moreover, as we demonstrate, the increased procurement of AI represents a component of a coherent technological bundle along with high resolution surveillance cameras and skilled labor in the police force which could complement AI and help the autocrat to maintain political control in the face of unrest.

4.2 The effect of AI procurement on suppressing unrest

We next examine whether greater AI procurement by the local governments' public security agencies effectively suppresses political unrest. Anecdotally, local governments appear to deploy facial recognition AI to reduce unrest through means such as identifying new faces in a protest, tracking suspicious persons in their daily life, or inducing deterrence among potential unrest participants.[29]

Importantly, having just demonstrated that AI procurement is endogenous to political unrest, we *cannot* direct estimate the impact of such endogenous AI procurement on subsequent political unrest. Estimating such a relationship is further challenged by the potential for strong autocorrelation over time in local political unrest.

To evaluate the impact of public security AI procurement on autocrats' political control, we thus examine how past public security AI procurement shapes the effects of external shocks on local political unrest. Consider a context in which multiple locations share a common elevated potential for political unrest, but experience different idiosyncratic weather conditions that shape the occurrence of unrest (as we have demonstrated in the LASSO IV first stage in the analysis above). In such a context, one may wonder whether pre-existing stock of AI technology procured by the public security agencies may mitigate the effect of favorable weather conditions on unrest occurrence.

To test this hypothesis, we estimate the effects of contemporaneous weather shocks in prefecture i at time t on local political unrest, allowing this effect to vary depending on the *lagged stock* of local public security procurement of AI up to period $t-1$, controlling for prefecture and time period (quarter) fixed effects. Specifically, we estimate the following

[29] For example, see "The Panopticon is Already Here" from the *Atlantic*, source: `https://bit.ly/3aWC1gB`.

model:

$$Unrest_{it} = \beta_1 AI\_stock_{i,t-1} + \beta_2 FineWeather_{it} + \beta_3 FineWeather_{it} \times AI\_stock_{i,t-1} \quad (2)$$
$$+ \alpha_t + \gamma_i + \delta_t X_i + \epsilon_{it}. \quad (3)$$

Table 4, Panel A, column 1, presents the baseline result. As can be seen, the estimated effect of fine weather is positive, indicating that fine weather is conducive to political unrest (as we have seen in previous section). However, the estimated effect of fine weather interacted with the stock public security AI procurement is negative: accumulation of AI capacity significantly weakens the positive relationship between fine weather and unrest occurrence, suggesting a role of AI in maintaining political control. In other words, unrest becomes less likely to take place in localities with higher public security AI capacity, when weather conditions are favorable and the localities experience similar potential to unrest. We continue to find qualitatively and quantitatively similar results as we gradually add time-varying controls to account for changes in local socioeconomic conditions (shown in columns 2-4). A one standard deviation increase in the stock of past public security AI procurement halves the effect of weather conditions conducive to political unrest.[30]

This empirical strategy relies on plausibly exogenous variation in weather conditions but endogenous variation in the lagged stock of AI procurement. We examine two potential sets of potential confounding variables related to the stock of AI — one regarding local governance and capacity more broadly and the other concerning past protests and changing local political dynamics and government responses. First, one might worry that past AI procurement for any purpose reflects local governments embracing new technology and more broadly the quality of local governance, which may in turn dampen political unrest. To address this concern, we conduct a placebo test: does past local AI procurement outside the public security agencies shape the relationship between local weather conditions and unrest occurrence? Crucially, the effect of past AI procurement only appears for the contracts issued by public security agencies. Local AI procurement by non-public security agencies does *not* mitigate the effects of fine weather on political unrest, as shown in Table 4, Panel B.[31] Second, since the cross-prefecture variation in previous AI procure-

[30]We again find qualitatively similar results for each sub-category of the unrest events (protests, public demands, and threats); see Appendix Table A.14. To the extent that these distinct event types are subject to different degrees of censorship in reporting of local unrest, this suggests that the results we find are unlikely to be explained by confounding factors that are correlated with both local governments' procurement of facial recognition AI technology and its use of censorship.

[31]Relatedly, one may also be concerned that deployment of facial recognition AI in response to unrest captures local politicians' strong career incentives, which could be associated with a range of other policies also aimed at suppressing subsequent unrest. To assess this possibility, we examine whether exogenous weather shocks have heterogeneous effects on contemporaneous unrest occurrence depending on local politicians' career incentives. We follow Wang et al. (2020) and estimate an index capturing each prefec-

ment is partially shaped by past political unrest (as shown above), if the past unrest is associated with heterogeneity in the locality's responses to subsequent weather shocks, this could confound the interpretation that results capture the effects of public security AI procurement.[32] To assess this possibility, we examine whether exogenous weather shocks have heterogeneous effects on contemporaneous unrest occurrence depending on past unrest in the locality. Specifically, we estimate specifications analogous to those described above, replacing $AI_s tock_{i,t-1}$ with $unrest_{i,t-1}$. As shown in Table 4, Panel C, we do not find a noticeable pattern of heterogeneous effects of fine weather depending on past unrest in the locality, suggesting that the pattern of heterogeneity we observe is likely due to public security AI procurement, rather than other mechanisms arising from past unrest *per se*.

Finally, we examine whether complementary technological investment increases the effectiveness of facial recognition AI in suppressing unrest. We estimate the baseline specification, replacing $AI\_stock_{i,t-1}$ with either the lagged stock of procurement of surveillance cameras $camera\_stock_{i,t-1}$ (Table 4, Panel D) or the interaction between the stock of AI and the stock of cameras $AI_s tock_{i,t-1} \times cameras_s tock_{i,t-1}$ (Panel E). We observe that while the stock of high resolution surveillance cameras alone does not effectively suppress subsequent unrest occurrence, when cameras are procured alongside facial recognition AI, the effectiveness of AI becomes amplified.

Taken together, these results suggest that the politically motivated procurement of AI technology is indeed useful in enhancing the state's political control capacity.

5 The role of autocratic political control in AI innovation

We now turn to the question of whether politically motivated procurement of AI stimulates AI innovation. Specifically, we focus on AI procurement contracts issued by public security agencies in prefectures that experienced above median levels of political unrest in the quarter prior to the contracts' issuance. As shown in the previous section, these contracts are plausibly issued for purposes of political control.

tural city leader's *ex ante* likelihood of promotion in each year, as a flexible function of their age (relative to retirement), tenure and official rank in the bureaucratic system (capturing the potential for upward mobility). As shown in Appendix Table A.5, we do not find a noticeable pattern of heterogeneous effects of fine weather depending on local politicians' career incentives.

[32]For example, past unrest may make subsequent unrest more likely (e.g., due to path-dependence), thus reducing the elasticity of unrest occurrence with respect to contemporaneous weather conditions. Alternatively, past unrest may reduce the likelihood of subsequent unrest (e.g., due to increased overall government repression independent of AI), thus also reducing the elasticity of unrest occurrence with respect to weather conditions.

We use a staggered event study design to identify the overall effects of procurement contracts issued for purposes of political control on the subsequent product development and innovation among the facial recognition AI firms that are awarded the contracts. The empirical strategy exploits variation across time and across firms in the receipt of a government contract, and across types of government contracts that firms receive.

As in an event study design, we compare firms' outcomes — their software releases — before and after they receive their first government contracts, controlling for firm and time period fixed effects.[33] Specifically, among firms receiving their first government contracts in a prefecture that recently experienced political unrest, we estimate the following specification:

$$y_{it} = \sum_{T} \beta_{1T} T_{it} + \alpha_t + \gamma_i + \delta_t X_i + \epsilon_{it}, \tag{4}$$

where T_{it} equals 1 if, at time t, T quarters have passed before/since firm i received its first public security contract; α_t are a full set of quarter fixed effects; and γ_i are a full set of firm fixed effects. The coefficients β_{1T} describe software production of a firm around the time when it receives its first politically motivated public security procurement contract.

In Figure 4, we plot the series of β_{1T} coefficients, considering the cumulative, total software output as well as output for government and commercial applications, respectively. In Panel A, one can see that firms receiving a public security contract issued following episodes of political unrest develop approximately 10 additional software products over the subsequent 2 years, representing an increase by 21.7%. One naturally wonders whether firms receiving public security contracts were already following a different trend of software production before the receipt of the contracts. However, we do not observe differential pre-contract software production levels or trends among firms that would go on to receive a public security procurement contract. We present event study coefficients from cumulative software production 8 quarters after contract in Table 5, column 1; we present the coefficients from a specification where we control for time-varying effects of an index of firms' pre-contract characteristics (firm size) and contract size in column 2; and we present coefficients from a weighted event study specification, following Borusyak et al. (2017), in column 3. The full set of event study coefficients are presented in Appendix Table A.6.

In Figure 4, Panels B and C, we decompose the software products into those intended for government and for commercial purposes, respectively. One observes that firms receiving public security procurement contracts following episodes of political unrest not

[33] We only examine firms' first contracts because subsequent contracts could be endogenous to firms' performance in the initial contracts.

only differentially produce more software for the government, but also increase their *commercial* software development. The differential increase in commercial software development totals around 5 additional software products over 2 years after the contract receipt, representing an increase of 26.6%. We present the full set of event study coefficients for commercial and government software in Appendix Tables A.7 and A.8. Again we observe no differential software production level or trend for either government or commercial categories prior to the receipt of the public security contracts, suggesting a causal interpretation. Our findings indicate a role for politically motivated government procurement in stimulating frontier innovation for both government and commercial applications.

One concern with this analysis is that our definition of politically motivated contracts relies on the endogenous occurrence of political unrest. Factors that shape political unrest may be associated with production of AI software specifically among firms that select into public security contracts (though recall that they are not generally local firms, so time and location-varying shocks do not directly drive these results). To address this concern, we alternatively define a politically motivated contract as a public security contract issued just after a quarter with above median *predicted* political unrest, using our weather-based LASSO instruments as described in Section 4. The estimated coefficients from this alternative definition of politically motivated contracts are plotted in darker-shaded dots in Figure 4, and presented in Table 5, columns 4-6 (see Appendix Table A.6, columns 4-6, for the full set of event study coefficients). One can see the effects of public security contracts on software innovation are very similar following episodes of plausibly exogenous political unrest.

Another concern is that the baseline specification may be capturing the effects of mechanisms other than the politically motivated pubic security contract *per se*. For example, firms receiving contracts in politically sensitive contexts (i.e., just following episodes of local unrest) may be specially selected in a way that may also be related to subsequent performance. These firms may also develop political connections (needed to receive a contract at a politically sensitive moment), which might affect subsequent performance. To address this concern, we compare the effects of public security contracts issued in a politically sensitive environment (defined as municipalities with above median political unrest in the previous quarter) with those of non-public security contracts issued in the same environment.[34] Specifically, among firms receiving their first government contracts in a prefecture that recently experienced political unrest, we estimate the following spec-

[34]The classification of a public security contract is only dependent on the agency issuing the contract; thus, public security contracts can be categorized as non-politically motivated if they were issued in a prefecture that had not experienced above-median unrest in the previous quarter.

ification:

$$y_{it} = \sum_T \beta_{1T} T_{it} + \sum_T \beta_{2T} T_{it} \times PublicSecurity_i + \alpha_t + \gamma_i + \delta_t X_i + \epsilon_{it}, \tag{5}$$

where $PublicSecurity_i$ is an indicator that the firm's first government contract is issued by a public security agency. The coefficients β_{1T} describe software production of a firm around the time when it receives its first government contract when this contract is issued by a non-public security agency; the sums of coefficients $\beta_{1T} + \beta_{2T}$ describe software production around the time when a firm receives its first government contract when this contract is issued by a public security agency; and the sequence of coefficients β_{2T} thus captures the differential software production before and after a firm receives a public security contract in a politically sensitive environment.

In Figure 5, we plot the series of β_{2T} coefficients; and in Appendix Tables A.9 - A.11, we present the full set of event study coefficients. Compared to firms receiving a non-public security contract issued in the same local political environment, we continue to observe, a positive and significant effects of politically motivated public security contracts on firms' total software production over the subsequent 2 years, as well as software intended for government and commercial purposes. We do not observe differential pre-contract software production levels or trends among firms that would go on to receive a public security procurement contract in a politically sensitive environment. Defining politically sensitive environments using the *predicted* level of political unrest based on our weather-based LASSO instruments (rather than observed unrest) yields very similar results.[35]

Robustness and ruling out alternative hypotheses

The results presented thus far do not appear to be the result of differential selection by firms into politically motivated public security procurement contracts. We find no evidence of pre-contract differences in software production levels or trends, which one would expect if firms selected into these contracts as a function of their underlying productivity. As an additional check, we flexibly control for the time-varying effects of firms'

[35] As an auxiliary test of the role of access to large quantities of government data collected out of political motivation, we examine whether firms receiving public security contracts in a politically sensitive environment develop data-complementary tools (e.g., software supporting data storage) to manage the large quantities of data that they receive access to. Importantly, these data-complementary software products are distinct from the AI software studied above. In Appendix Figure A.14, we present estimates from the same specification as in Figure 5, but now considering the outcome of data-complementary software products. One can see that data-complementary software production differentially increases after the receipt of a public security contract in a politically sensitive environment, relative to the receipt of a non-public security contract.

age and pre-contract software production, in order to address concerns about firms selecting into contracts as a function of their potential production growth (see Appendix Tables A.12 - A.13, Panels A.2 and A.3). Moreover, by flexibly controlling for the time-varying effects of firms' pre-contract capitalization as well as the dollar value of the contracts, we also account for selection into these contracts on firms' potential benefit from the capital that the contracts provide (see Panels A.4 and A.5).[36] The results are qualitatively and quantitatively similar across these alternative specifications.

We next assess the robustness of our results to variation in specifying our outcome of interest — measures of software innovation. We restrict attention only to firms' new software releases (i.e., version 1.0) and major upgrades with a change in the first digit of the release number (i.e., versions 2.0, 3.0, etc.). Our baseline estimates remain largely unchanged, indicating that our results are not driven by minor software updates (see Panel B).

Given the complex process of constructing our dataset, it is important to note that our findings are robust to varying several salient dimensions of our analysis (see Appendix Tables A.12 - A.13, Panels C - E). First, our results are robust to adjusting our classification of public security contracts to exclude any government contracts ambiguously related to public security (e.g., contracts with the government headquarters and smart city management and administrative bureaux could be meant to provide security services just for the government office building; see Panel C). Second, the results are robust to adjustments of the parameters of the machine learning algorithm used to classify software — timestep, embedding, and nodes of the RNN LSTM model (see Panel D). Third, our results are robust to considering a balanced panel of firms within a narrow window, and to expanding the window of time around the receipt of the first contract that we study (see Panel E).

Our results are also maintained under specifications that help us address a range of alternative hypotheses. One concern is that contracts with the public security agencies within the powerful, high-surveillance local governments of Beijing or Shanghai may not generalize to the broader range of politically-motivated contracts. To rule out the possibility that our findings are distorted by contracts with these two local governments, we estimate our baseline specification, but add fixed effects for contracts from Beijing and Shanghai governments interacted with a full set of quarter to/from contract fixed effects (see Panel F.1). Results are also robust to dropping contracts from the surveillance-intensive province of Xinjiang (see Panel F.2). We additionally account for a firm's home

[36]The inclusion of the financial value of the contract as a control variable shuts down one mechanism through which politically motivated contracts shape innovation, and is thus arguably over-controlling for unobserved drivers of firms' selection into contracts.

prefecture/province government potentially giving the firm a commercial advantage beyond the procurement contracts themselves by estimating the baseline model excluding contracts signed between firms and any government in their home prefecture/province (see Panels F.3 and F.4). Moreover, to address a broader set of concerns about time and space varying shocks that may drive firms' commercial activities, we control for province by quarter fixed effects and show that results are qualitatively similar (see Panel G). Finally, we consider software in a field of AI that is considered most difficult and frontier in its application, video-based facial recognition, which (as opposed to static images) requires N-to-1 or even N-to-N matching algorithms, and we find qualitatively similar results (see Panel H).

Software export activities

Firms' export activities are often considered a signal of production at the technological frontier (Vernon, 1966; Melitz, 2003; Filatotchev et al., 2009).[37] We link firm-level data on export deals to the procurement contracts awarded to these firms, and we test whether receipt of a politically-motivated public security contract is associated with a change in a firm's status as an AI exporter. We compare the change in exporter status for firms receiving politically motivated public security contracts with firms receiving non-public security contracts in a politically sensitive environment to account for firm selection and the role of firms' political connections. We examine the cross sectional relationship between a change in exporter status around contract receipt, finding a significantly larger change among firms receiving a politically motivated public security contract. This is seen in the raw data (Table 6, column 1), as well as accounting for contract quarter fixed effects, contract prefecture fixed effects, firms' pre-contract software production, as well as firms' age (columns 2-4). We observe a robust pattern that firms receiving politically motivated contracts are more likely (by 3.2 to 3.9 percentage points) to become exporters following receipt of these contracts. This effect is large: among AI firms who won at least one politically motivated public security contract, only 1% of them have exported their products during 2014 and 2021.

Firm-level distortions due to politically motivated contracts To the extent that politically motivated public security contracts may be accompanied by additional, non-commercial demands from the local government, or may be associated with greater spe-

[37]Production at the technological frontier does not necessarily imply that a firm is substantially shifting the frontier. The new products we study here are examples of micro-innovations, rather than macro-inventions to use the terminology of Mokyr (1990).

cialization, such contracts could differentially crowd out firms' commercial activities relative to the public security contracts that are not politically motivated, but which provide access to similar resources (e.g., data, capital, and political connections).[38] As discussed in Beraja et al. (2021), the greater the effects of politically motivated contracts on software production for the more general commercial market, the greater the impact these contracts would have on the trajectory of innovation in the AI sector.

To evaluate whether politically motivated contracts are associated with differential crowding out of commercial innovation, we compare the effects of politically motivated public security contracts to the effects of non-politically motivated public security contracts. We define politically motivated contracts as those issued following a quarter with above median political unrest (as we did above), and politically neutral contracts as those issued following a quarter with below median political unrest. We now limit our analysis only to public security contracts, and compare effects on software output of those granted out of political motivation with those that are politically neutral.

Appendix Figure A.15 presents the coefficients indicating the differential effect of politically motivated public security contracts for the AI firms' commercial software production. We do not observe noticeable crowd-out of politically motivated contracts. In fact, if anything, one sees that politically motivated contracts tend to induce firms to produce more commercial software especially towards the later periods of the sampling frame.

Cross-firm spillovers and aggregate effects

We next consider the aggregate effects of politically motivated contracts. These may differ from the firm-level effects that we identify above due to either positive or negative spillovers to other firms not receiving contracts. Positive spillovers across firms might arise due to knowledge spillovers from contracted firms to others (or across subsidiaries within the same mother firm). These spillovers may occur primarily in the locations where unrest occurs, or where contracted firms are headquartered and innovative activities may be concentrated. On the contrary, negative spillovers may arise if critical resources such as investments and human capital are disproportionally allocated to firms that have been awarded procurement contracts, or due to business stealing effects among firms in the industry or across subsidiaries.

Gauging such spillovers along three margins, we examine AI innovation among firms *never* receiving procurement contracts that are: *(i)* headquartered in localities that have experienced political unrest; *(ii)* headquartered in localities where AI firms receiving po-

[38] This could arise from fixed costs associated with developing products specifically for politically sensitive and demanding environments.

litically motivated contracts are also headquartered; or *(iii)* part of a mother firm with other subsidiaries that have received politically motivated contracts.[39]

Specifically, we estimate event study models in which the innovation of firms that never receive contracts is examined around: *(i)* a quarter when local prefecture experiences political unrest; *ii* a quarter when a politically motivated public security contract is issued to other firms headquartered in the same prefecture; and *(iii)* a quarter when a politically motivated public security contract is issued to another subsidiary of the same mother firm. We present the cumulative spillover effects two years after the relevant events in Table 7, Panels A to C, respectively; we plot the full event study estimates from two years leading up to the event to two years after in Appendix Figure A.16. We find no evidence of negative spillovers in any of these cases. In fact, we find suggestive evidence of positive spillovers to the amount of commercial software produced by non-contracted firms.

While these tests are not absolutely conclusive, the absence of evidence of significant distortions — both at the firm level and across firms — as a result of autocrats' politically motivated procurement of AI technology suggests a positive aggregate effect on frontier AI innovation.[40]

6 Concluding thoughts: the implications of AI-tocracy

We document a mutually reinforcing relationship between facial recognition AI innovation and China's autocratic regime. This relationship has direct implications both for China's economic and political trajectories. First, China's autocratic politics may not constrain its ability to continue to push out the technological frontier in AI: rather, frontier innovation in AI may be stimulated precisely because of China's autocratic politics. Second, continued frontier innovation and economic development in China may not be associated with more inclusive political institutions: rather, such innovation may further entrench the autocratic regime.

It is important to consider the extent to which our results generalize. While many technologies would not exhibit forces that generate mutually reinforcing relationships between autocracy and frontier innovation, the key forces that we highlight could shed

[39]These three margins are not intended to be an exhaustive catalog of spillovers, but rather the important ones that we have empirical traction to evaluate. In addition, firms not receiving contracts may be either positively or negatively affected by broader local policy changes enacted in response to local unrest.

[40]It is however important to note that by examining only firms in facial recognition AI, we are unable to investigate whether the increased frontier innovation in facial recognition AI imposes costs on AI innovation in directions other than facial recognition, or other fields beyond AI as a whole.

light on prominent historical episodes of frontier innovation in, for example, the USSR and Imperial Germany. More generally, the evidence also speaks to how state-sponsored innovation is supported in democracies, including innovation supported by DARPA in the US, the high-tech sector supported by the military in Israel, and nuclear engineering programs led by the French state.

Looking ahead, a mutually reinforcing relationship between AI and autocracy may become relevant in other contexts. Russia, in particular, has already deployed facial recognition AI for purposes of political control, and (not coincidentally) alongside China is among the world's leading producers of frontier facial recognition AI technology.[41] Moreover, autocrats in other countries well inside the technological frontier may import Chinese AI technology for purposes of political control. Indeed, anecdotal evidence suggests that China's surveillance AI technology has already been exported to other autocracies.[42] One thus naturally worries that autocrat-supporting AI may beget more autocracies. The implications of China's AI innovation for the global political and economic landscape are worthy of further, rigorous investigation.

[41] Appendix Figure A.17 presents the global ranking of the companies who have the top 10 facial recognition algorithms in terms of prediction accuracy, as ranked by the Face Recognition Vendor Test (FRVT), organized by the National Institute of Standards and Technology (NIST, an agency of the US Department of Commerce) and considered as one of the most authoritative AI industry competitions. Chinese firms occupy all of the top 4 positions; 5 out of the top 10 positions are occupied by Chinese and Russian firms. Regarding Russia's use of facial recognition for political control, see, for example, "In Moscow, Big Brother Is Watching and Recognizing Protesters" by Bloomberg, source: `https://bloom.bg/3tmtsSG`.

[42] For example, according to an Atlantic article, "Xi Jinping is using artificial intelligence to enhance his government's totalitarian control — and he's exporting this technology to regimes around the globe [...] China is already developing powerful new surveillance tools, and exporting them to dozens of the world's actual and would-be autocracies." Source: `https://bit.ly/3ujqj7g`.

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Panel A: Unrest events

Panel B: Public security AI contracts

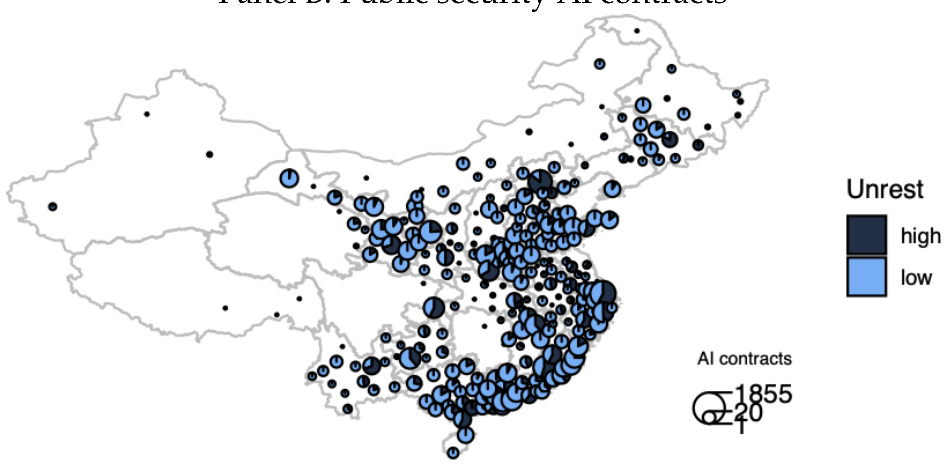


Figure 1: Each circle represents a prefecture in our dataset that has at least one public security AI contract that is an AI firm's first government contract. In Panel A, circle size indicates the number of unrest events in a prefecture, while in Panel B, circle size indicates the number of public security AI contracts awarded in the prefecture (larger circles indicate more, log scale). Circle shading in Panel B indicates the fraction of first AI contracts that were procured during high or low unrest periods, where the within-prefecture variation comes from changes in the number of unrest events in a prefecture over time (a larger fraction of dark shading indicates a larger fraction of prefecture contracts procured during high unrest periods).

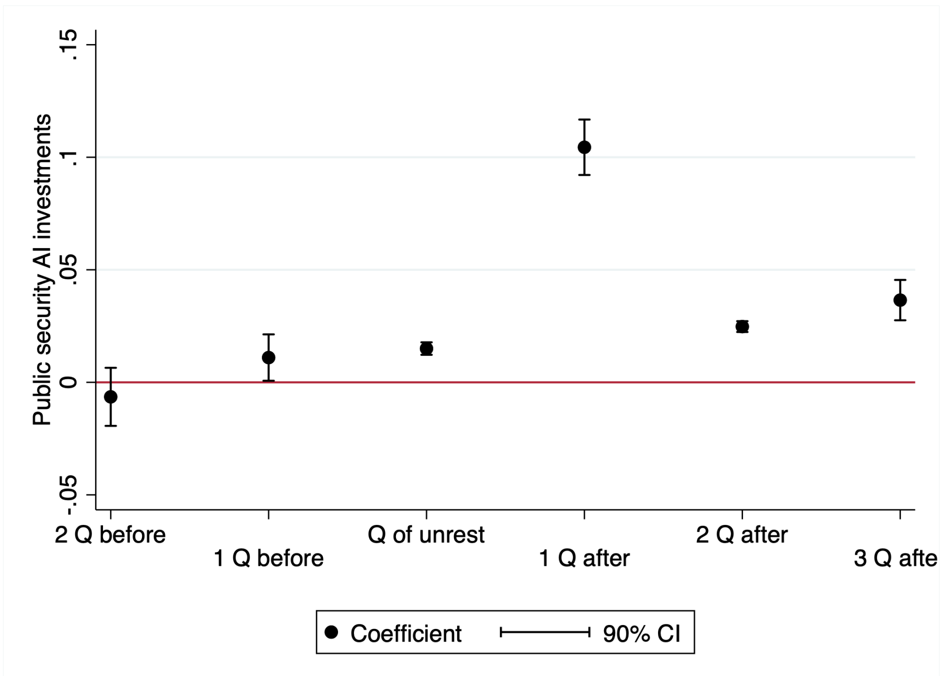


Figure 2: Public security AI investments relative to the quarter of political unrest. This figure plots the estimated effects of leads and lags of prefecture political unrest on prefecture public security AI procurement from a regression that also includes quarter and prefecture fixed effects. The outcome (AI procurement) and explanatory variables of interest (unrest events) are standardized to mean = 0, variance = 1.

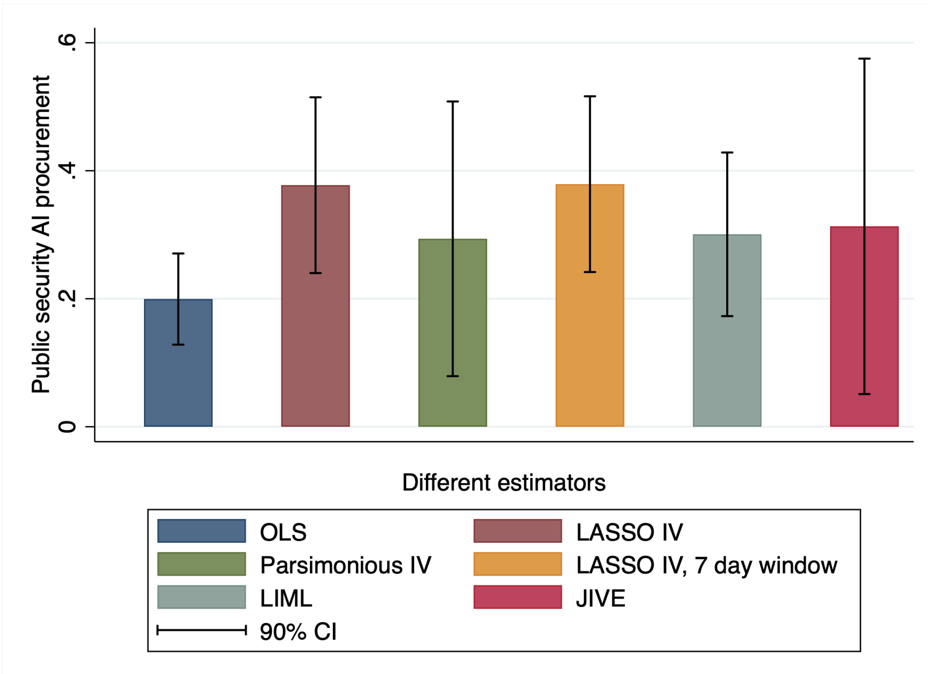
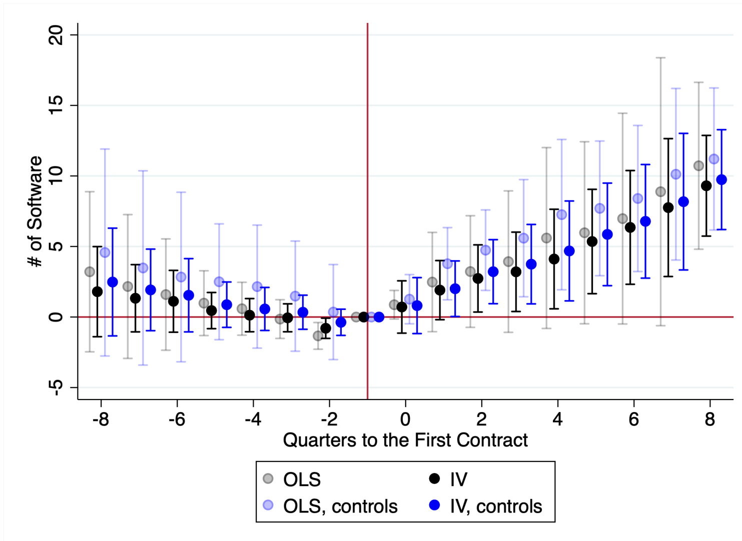
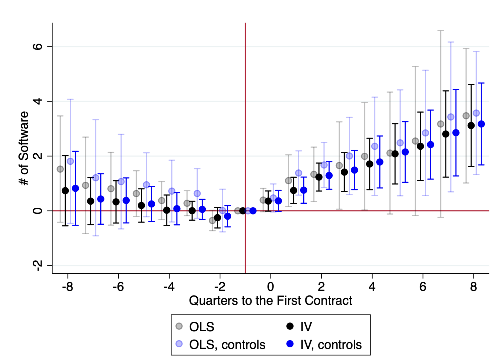


Figure 3: Public security AI investments in the quarter after political unrest. The OLS bar chart and confidence interval shows the amount of public security AI investments made in the quarter after political unrest at the prefecture-quarter level (see Table 2, Panel A, column 1). The LASSO IV instruments for unrest using a cross-fit partialing-out LASSO IV algorithm on weather variables interacted with themselves and an indicator for whether unrest occurred elsewhere in China on the day (see Table 2, Panel B, column 1). The parsimonious IV replicates this specification using a more parsimonious set of weather variables (interacting rain, thunder, and wind with unrest on the day). The LASSO IV, 7 day window expands the first stage window for unrest to one week instead of limiting it to the same day. LIML and JIVE replicate the same specification using these alternate estimators, including the same instruments used by LASSO. All specifications include prefecture and quarter fixed effects. The outcome and independent variables are standardized to mean = 0, variance = 1.

Panel A: Total



Panel B: Government



Panel C: Commercial

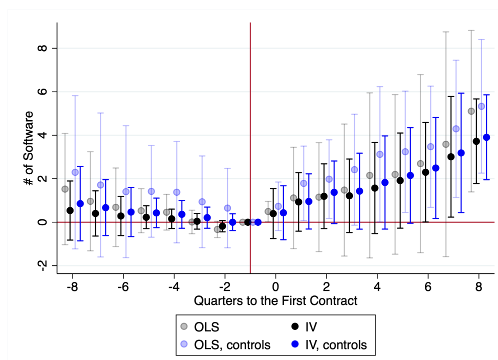


Figure 4: Effects of politically motivated contracts on total software development (Panel A), software developed for government applications (Panel B), and software developed for commercial applications (Panel C) relative to the time of receiving initial contract. All panels restrict firms to those that receive contracts in prefectures experiencing above-median political unrest (or predicted unrest) in the previous quarter, and control for firm and time period fixed effects. Black lines/markers show the total effect over time for firms. Blue lines/markers add controls for an inverse covariance weighted index of firm productivity containing contract size and company size. Dark lines/markers use LASSO selected weather variables to instrument for unrest.

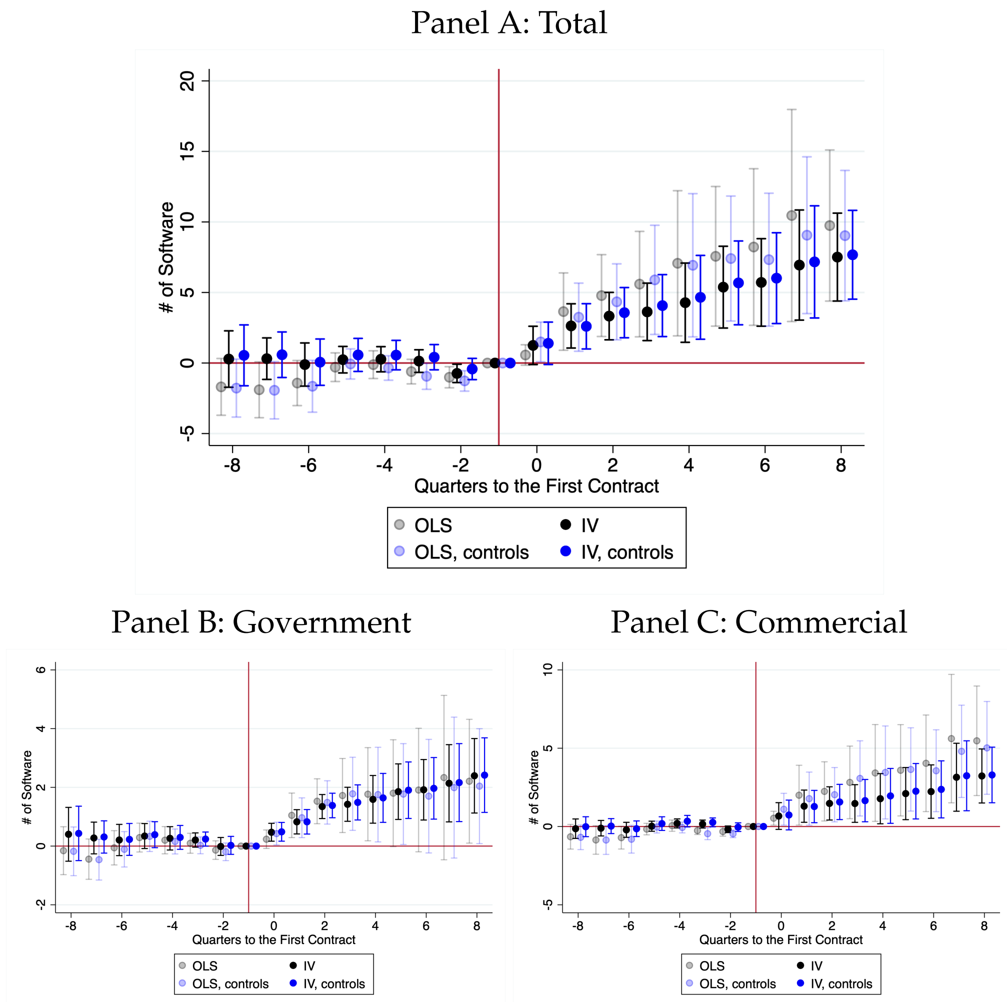


Figure 5: Differential effects of politically motivated contracts on total software development (Panel A), software developed for government applications (Panel B), and software developed for commercial applications (Panel C) by firms that receive public security contracts versus non-public security ones, relative to the time of receiving the initial contract. All panels restrict firms to those that receive contracts in prefectures experiencing above-median political unrest (or predicted unrest) in the previous quarter, and control for firm and time period fixed effects. Black lines/markers show the total effect over time for firms. Blue lines/markers add controls for an inverse covariance weighted index of firm productivity containing contract size and company size. Dark lines/markers use LASSO selected weather variables to instrument for unrest.

Table 1: Summary statistics

	Mean	S.D.
	(1)	(2)
Panel A: Political unrest		
All events (per prefecture-quarter)	2.419	18.490
Protests	0.607	4.603
Demands	0.720	5.009
Threats	1.092	9.479
Panel B: Procurement of AI and the technology of political control		
All AI contracts (per prefecture-quarter)	3.976	7.818
Non-public security contracts	2.285	5.118
Public security contracts	1.691	3.476
First public security contracts	0.082	0.327
Surveillance cameras (per prefecture-quarter)	2,118	12,684
Police hires (per prefecture-year)	59.278	84.991
Panel C.1: Innovation of AI firms (flow)		
All software (per firm-quarter)	5.756	7.124
Government software	1.724	3.337
Commercial software	2.353	3.675
Data-complementary software	2.273	3.605
Panel C.2: Innovation of AI firms (cumulative, pre-contract)		
All software (per firm)	22.105	33.004
Government software	6.266	11.738
Commercial software	9.333	15.936
Data-complementary software	8.633	14.374

Notes: This table presents summary statistics at the prefecture-quarter level (firm-quarter and firm level for Panels C.1 and C.2) for variables of interest. Column 1 shows the sample mean and column 2 the standard deviation. Panel A presents counts of unrest events, Panel B presents counts of local government-procured facial recognition AI contracts and other technologies of political control, Panel C.1 presents counts of software produced by facial recognition AI firms per quarter (a flow variable), and Panel C.2 presents counts of cumulative software produced by facial recognition AI firms up to the quarter before earning a contract. For Panels A and B, $N = 8,167$ (Panel B police hires, $N = 2,672$). For Panel C.1, N = 23,697. For Panel C.2, N = 5,462.

Table 2: Effect of unrest events on facial recognition AI procurement

	Public security AI procurement			
	(1)	(2)	(3)	(4)
Panel A: OLS				
Unrest events$_{t-1}$	0.199***	0.198***	0.199***	0.200***
	(0.043)	(0.045)	(0.044)	(0.043)
Panel B: Lasso IV				
Unrest events$_{t-1}$	0.375***	0.383***	0.375***	0.375***
	(0.085)	(0.085)	(0.085)	(0.085)
GDP $\times$ quarter	Yes	No	No	Yes
Log population $\times$ quarter	No	Yes	No	Yes
Gov. revenue $\times$ quarter	No	No	Yes	Yes

Notes: This table presents regressions at the prefecture-quarter level. The outcome is the number of public security facial recognition AI contracts procured by the local government, standardized to mean = 0 and variance = 1. The explanatory variable of interest is the occurrence of unrest events in the corresponding prefecture during the preceding quarter, also standardized. Column 1 controls for prefecture GDP x quarter effects, column 2 controls for log prefecture population x quarter effects, column 3 controls for prefectural government tax revenue x quarter effects, and column 4 includes all controls. Panel A presents OLS regression estimates. Panel B presents a cross-fit partialing-out LASSO IV specification: we instrument for unrest events using weather variables interacted with themselves and an indicator for whether an unrest event occurred elsewhere in China on the day (variables are selected by LASSO), aggregated to the quarter level. All specifications include prefecture and quarter fixed effects. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3: Effect of unrest events on surveillance camera and facial recognition AI procurement

	Public security AI/camera procurement			
	(1)	(2)	(3)	(4)
Panel A.1: OLS, cameras				
Unrest events$_{t-1}$	0.436***	0.420***	0.436***	0.423***
	(0.084)	(0.083)	(0.085)	(0.078)
Panel A.2: Lasso IV, cameras				
Unrest events$_{t-1}$	0.635***	0.620***	0.635***	0.621***
	(0.185)	(0.181)	(0.185)	(0.180)
Panel B.1: OLS, AI X surveillance cameras				
Unrest events$_{t-1}$	0.681***	0.669***	0.680***	0.674***
	(0.154)	(0.157)	(0.155)	(0.150)
Panel B.2: Lasso IV, AI X surveillance cameras				
Unrest events$_{t-1}$	1.058***	1.074***	1.058***	1.058***
	(0.380)	(0.383)	(0.380)	(0.380)
GDP $\times$ quarter	Yes	No	No	Yes
Log population $\times$ quarter	No	Yes	No	Yes
Gov. revenue $\times$ quarter	No	No	Yes	Yes

Notes: This table presents regressions at the prefecture-quarter level. The outcome in Panel A is the number of surveillance cameras procured by the local government. The outcome in Panel B is the product between the number of public security facial recognition AI contracts procured by the local government and the number of surveillance cameras procured by the corresponding government. Outcome variables in Panels A and B are standardized to mean = 0 and variance = 1. The explanatory variable of interest is the occurrence of unrest events in the corresponding prefecture during the preceding quarter, also standardized. Column 1 controls for prefecture GDP x quarter effects, column 2 controls for log prefecture population x quarter effects, column 3 controls for prefectural government tax revenue x quarter effects, and column 4 includes all controls. Panels A.1 and B.1 present OLS regression estimates. Panels A.2 and B.2 present a cross-fit partialing-out LASSO IV specification: we instrument for unrest events using weather variables interacted with themselves and an indicator for whether an unrest event occurred elsewhere in China on the day (variables are selected by LASSO), aggregated to the quarter level. All specifications include prefecture and quarter fixed effects. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.

Table 4: Effect of AI procurement on suppressing unrest

	Standardized number of unrest events			
	(1)	(2)	(3)	(4)
Panel A: Procurement of public security AI				
Favorable weather	0.9176***	0.9523***	0.9183***	0.9511***
	(0.1609)	(0.1597)	(0.1613)	(0.1543)
Public security procurement stock AI_{t-1}	-0.0080**	-0.0032	-0.0079**	-0.0020
	(0.0039)	(0.0050)	(0.0038)	(0.0050)
Favorable weather × public security AI_{t-1}	-0.2265*	-0.2729**	-0.2260*	-0.2662**
	(0.1153)	(0.1306)	(0.1156)	(0.1250)
Panel B: Procurement of non-public security AI				
Favorable weather	0.9378***	0.9768***	0.9385***	0.9747***
	(0.1678)	(0.1666)	(0.1682)	(0.1608)
Non-public security procurement stock AI_{t-1}	-0.0021*	-0.0022	-0.0021*	-0.0019
	(0.0012)	(0.0014)	(0.0012)	(0.0012)
Favorable weather × non-public security AI_{t-1}	-0.0441	-0.0513	-0.0444	-0.0473
	(0.0299)	(0.0338)	(0.0305)	(0.0301)
Panel C: Weather shock and local unrest at $t-1$ on local unrest				
Favorable weather	0.9770***	0.9813***	0.9777***	0.9798***
	(0.1660)	(0.1711)	(0.1664)	(0.1656)
Unrest_{t-1}	0.0002	-0.0006	0.0038	0.0013
	(0.0672)	(0.0706)	(0.0684)	(0.0664)
Favorable weather × unrest_{t-1}	-0.0110	-0.0114	-0.0120	-0.0114
	(0.0187)	(0.0195)	(0.0189)	(0.0186)
Panel D: Procurement of surveillance cameras				
Favorable weather	0.9175***	0.9563***	0.9183***	0.9560***
	(0.1540)	(0.1548)	(0.1544)	(0.1501)
Surveillance camera procurement stock cam_{t-1}	-0.0090	-0.0068	-0.0091	-0.0066
	(0.0186)	(0.0171)	(0.0186)	(0.0166)
Favorable weather × surveillance cam_{t-1}	0.0574	0.0497	0.0573	0.0485
	(0.0790)	(0.0724)	(0.0790)	(0.0706)
Panel E: Procurement of public security AI X surveillance cameras				
Favorable weather	0.9113***	0.9446***	0.9118***	0.9449***
	(0.1585)	(0.1560)	(0.1587)	(0.1517)
Public security procurement stock cam. and AI_{t-1}	0.2462**	0.2734***	0.2455**	0.2638***
	(0.1074)	(0.0997)	(0.1073)	(0.0945)
Favorable weather × public security cam. and AI_{t-1}	-0.5688**	-0.6598***	-0.5735**	-0.6403***
	(0.2281)	(0.2401)	(0.2304)	(0.2229)
GDP × quarter	Yes	No	No	Yes
Log population × quarter	No	Yes	No	Yes
Gov. revenue × quarter	No	No	Yes	Yes

Notes: This table presents regressions at the prefecture-quarter level. The outcome of interest is the number of political unrest events in the prefecture in a given month, standardized to mean = 0 and variance = 1. Favorable weather is the standardized number of predicted unrest events (aggregated to the quarter level) from the LASSO specification. The stock of public security AI, non-public security AI, surveillance camera procurement, and local unrest in the quarter prior to the unrest events are also standardized to mean = 0 and variance = 1. Column 1 controls for prefecture GDP × quarter fixed effects, column 2 controls for log prefecture population × quarter fixed effects, column 3 controls for prefectural government tax revenue × quarter fixed effects, and column 4 includes all prior controls. All specifications include prefecture and quarter fixed effects. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.

Table 5: Total effect of politically-motivated public security contracts on software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total software						
8 quarters after contract	10.746***	11.245***	13.149***	9.258***	9.673***	11.114***
	(3.917)	(3.313)	(3.059)	(2.072)	(2.071)	(1.926)
Panel B: Government software						
8 quarters after contract	3.441**	3.538**	4.191***	3.115***	3.171***	3.755***
	(1.497)	(1.361)	(1.363)	(0.900)	(0.898)	(0.943)
Panel C: Commercial software						
8 quarters after contract	5.090**	5.318***	5.976***	3.728***	3.903***	4.374***
	(2.293)	(1.906)	(1.794)	(1.161)	(1.175)	(0.958)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in total software production between firms that earn politically motivated (public security) contracts versus firms that do not earn a contract. Panel A uses total software production as the outcome, Panel B uses government software, and Panel C uses commercial software. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). The full coefficients can be found in Appendix Tables A.6 - A.8. Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table 6: Effect of public security AI contract on AI exports

	Newly exporting firm			
	(1)	(2)	(3)	(4)
Public security	0.032*	0.036**	0.039**	0.036**
	(0.018)	(0.017)	(0.019)	(0.018)
Contract quarter FE	No	Yes	Yes	Yes
Contract prefecture FE	No	Yes	Yes	Yes
Pre-contract software	No	No	Yes	Yes
Firm age	No	No	No	Yes

Notes: This table presents cross-sectional regressions at the firm level. The dependent variable is an indicator of whether the firm begins to export its AI products after receiving its first contract (i.e., the first difference in firm exporting status around the time of receiving a first government contract). The explanatory variable of interest is an indicator of whether the first contract was a (politically-motivated) public security contract. The sample includes firms receiving their first contracts in prefectures that experienced above median political unrest in the preceding quarter. Column 1 presents a simple regression; column 2 adds contract quarter and contract prefecture FEs; column 3 adds a control for firms' pre-contract software output; and column 4 adds a control for firms' age. Firms are weighted by their number of subsidiary firms. Robust standard errors are reported in parentheses. * significant at 10% ** significant at 5% *** significant at 1%.

Table 7: Aggregate effects of politically-motivated public security contracts on software production

	Software produced		
	Total software	Government	Commercial
	(1)	(2)	(3)
Panel A: Firms headquartered in localities that experienced political unrest			
8 quarters after unrest	23.968**	1.372	9.812**
	(10.122)	(1.102)	(4.709)
Panel B: Firms headquartered in localities where AI firms receiving politically motivated contracts are also headquartered			
8 quarters after contract	0.055	0.029	0.030
	(0.077)	(0.031)	(0.035)
Panel C: Firms that are part of a mother firm with other subsidiaries that have received politically motivated contracts			
8 quarters after contract	0.371	-0.042	0.548**
	(0.306)	(0.177)	(0.223)

Notes: The table presents regression coefficients for facial recognition AI firms who are proximate to other firms that receive politically motivated public security contracts. Firms that receive politically motivated public security contracts are defined as: firms that are headquartered in prefectures that experience above median amounts of political unrest in Panel A, firms headquartered in prefectures where other AI firms that have received politically motivated contracts are headquartered in Panel B, or firms that belong to mother firms whose other subsidiaries have received politically motivated contracts in Panel C. The table shows the difference in total software production between firms awarded politically motivated (public security) contracts versus firms that are not awarded a contract. All columns control for time period fixed effects and firm fixed effects. Panels B and C additionally control for contract fixed effects. Column 1 uses total software production as the outcome, column 2 uses government software, and column 3 uses commercial software. Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

ONLINE APPENDIX

Appendix A Historical episodes of frontier innovation in non-democratic regimes

We first consider the success of scientific innovation in the Soviet Union, which was world leading in areas such as physics, mathematics, and aerospace and nuclear engineering. A striking feature of Soviet politics is the role of scientific advancement in legitimizing the Communist regime.[1] Science served as an effective propaganda tool, both internally and externally, to enhance the prestige and legitimacy of the regime. For example, following the launch of Sputnik (the first satellite), *Pravda* celebrated "how the freed and conscientious labor of the people of the new socialist society makes the most daring dreams of mankind a reality" (Pravda, 1957). Scientific advancement also generated military technology that strengthened the regime against both internal and external threats: from nuclear warheads to Intercontinental Ballistic Missiles to fighter jets. The Soviet state's financial and institutional support of science produced the world's largest community of scientists and engineers (Graham, 1989, 2013).[2] It also produced remarkable technological achievements, most famously in the space program, which launched the first satellite, sent the first human into space, constructed the first space station, and captured the first image of the far side of the moon, among other accomplishments.

A second case of frontier innovation under a non-democratic regime is the Second German Empire, which emerged as a powerhouse of science, industrialization, and innovation in the late 19th century.[3] Scientific and engineering innovation in many sectors were considered critical to ensure that Germany had a leading position among the imperial powers of Europe, not least because such innovation directly strengthened German military and naval capacity. For example, when describing the aim of the soon-to-be-established Imperial Institute of Physics, an imperial official stated that "there can be no doubt that our navy, telegraph system, survey organization, army and even the railways will [...] to a considerable degree be dependent on the results of the research for which this Imperial Institute of Physics is intended." Such imperial research institutes combined the expertise of German scientists with large amounts of state funding, producing not only military technology, but also general (even Nobel Prize-winning) scientific and industrial innovations. The eminent industrialist Von Siemens credited these institutes with Germany's industrial development, writing, "we have only the high quality of scientific education in Germany to thank for the fact that German industry, despite unfavorable circumstances, has somehow managed to retain its prominent position."

Apart from these two prominent episodes, one observes other instances of frontier innovation taking place in non-democratic regimes. In some cases, frontier technology

[1] The importance of science to Communist ideology is seen in the Soviet government's "official view that science and Soviet socialism are mutually supportive" (Graham, 1989; see also Ings, 2017 and Slezkine, 2017).

[2] We do not claim that the Soviet's support of science and innovation was without distortion. Ings (2017) describes costly political distortions to science under Stalin.

[3] We rely on Pfetsch (1970) throughout this case study.

enhances the legitimacy of the state, as in the Soviet example described above. For example, in Socialist Cuba, the remarkable success of the health care sector (e.g., developing vaccines and cancer treatments) served to bolster the regime's claim of political legitimacy (Geloso et al., 2020). In other cases, frontier innovation strengthens the regime through stimulating the economy and developing military technologies, as in the German example described above. Much like Germany, Imperial Japan post-Meiji Restoration heavily invested in frontier innovation in order to industrialize and strengthen its military capacity (Morris-Suzuki, 1994). Singapore has since its independence actively supported export-oriented industrial innovation, the success of which fueled its growth miracle and helped entrench its one-party rule (Yue, 2005).

The two directions of the mutually reinforcing relationship between frontier innovation and autocracy appear to be shared across these episodes. First, the non-democratic regimes appear to derive political power from frontier innovation. Second, recognizing the political benefits of innovation, the regimes provide financial and institutional support that may be instrumental to technical development.

Appendix B Auxiliary data sources

In addition to the primary data sources described in Section 3, we also use a number of auxiliary data sources for the empirical analysis.

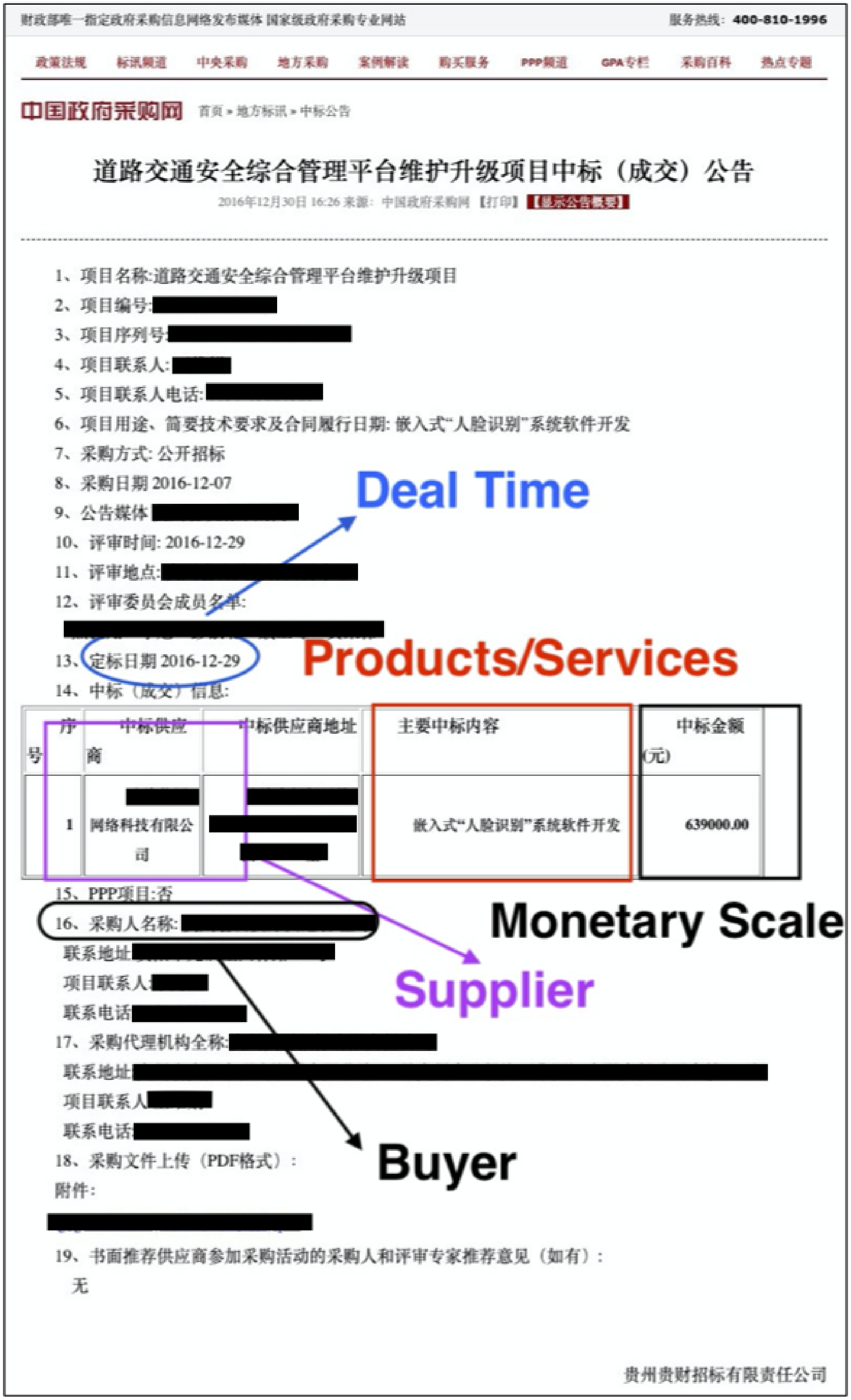
Local governments' procurement of surveillance cameras In addition to the public security procurement of AI technology, we also observe local governments' investments in two complementary technologies for public security purposes. First, we identify local public security units' procurement of high-resolution surveillance cameras, which are capable of collecting data for any AI control systems that may be in place. We construct a panel of the number of surveillance cameras in a given prefecture at the monthly level; when the number of cameras purchased in a given contract is not disclosed, we use the monetary value of the contract to impute the number of cameras purchased. In total, we identify 17,306 public security procurement contracts for surveillance cameras; during the period between 2013 and 2019, the average prefecture purchased 60,437 surveillance cameras (median = 20,439 and standard deviation = 117,672).

Local governments' police hiring Second, we collect data on personnel hiring by local police departments. From the website of OffCN Education Technology, we collect comprehensive listings of the number of police officers' job openings posted and filled by each department in a given year.[4]

Using job-specific details, we are able to observe changes in police department hiring composition over time, by classifying new police hires into "field jobs" (e.g., police on the street) that require lower human capital, and "office jobs" (e.g., police working in the office) that require higher human capital. There are approximately 15,500 unique job positions to classify. We manually classify the 2,000 most common jobs as either field or office based on the job's title, description and requirements, and use keyword matching to classify the remainder. During the period of 2013 to 2019, the average local police department makes 32 hires in a year, of which 14 hires are for desk jobs.

[4]OffCN Education Technology is a private firm providing labor market services specializing in the public sector; see `http://sd.offcn.com/` for details.

Appendix C Additional figures and tables



财政部唯一指定政府采购信息网络发布媒体 国家级政府采购专业网站　　服务热线：400-810-1996

政策法规　标讯频道　中央采购　地方采购　案例解读　购买服务　PPP频道　GPA专栏　采购百科　热点专题

中国政府采购网　首页 » 地方标讯 » 中标公告

道路交通安全综合管理平台维护升级项目中标（成交）公告

2016年12月30日 16:26 来源：中国政府采购网 【打印】【显示公告概要】

1、项目名称:道路交通安全综合管理平台维护升级项目
2、项目编号:[redacted]
3、项目序列号:[redacted]
4、项目联系人:[redacted]
5、项目联系人电话:[redacted]
6、项目用途、简要技术要求及合同履行日期: 嵌入式"人脸识别"系统软件开发
7、采购方式: 公开招标
8、采购日期 2016-12-07
9、公告媒体 [redacted]
10、评审时间: 2016-12-29
11、评审地点:[redacted]
12、评审委员会成员名单:
[redacted]
13、定标日期 2016-12-29
14、中标（成交）信息:

序号	中标供应商	中标供应商地址	主要中标内容	中标金额(元)
1	[redacted] 网络科技有限公司	[redacted]	嵌入式"人脸识别"系统软件开发	639000.00

15、PPP项目:否
16、采购人名称:[redacted]
联系地址 [redacted]
项目联系人 [redacted]
联系电话 [redacted]
17、采购代理机构全称:[redacted]
联系地址 [redacted]
项目联系人 [redacted]
联系电话 [redacted]
18、采购文件上传（PDF格式）：
附件:
[redacted]
19、书面推荐供应商参加采购活动的采购人和评审专家推荐意见（如有）：
无

贵州贵财招标有限责任公司

Figure A.1: Example of a procurement contract record; source: Chinese Government Procurement Database.

Figure A.2: Example of AI firm record from *Tianyancha* (excerpt).

Highlights

Employees
1,000
As of 24-Oct-2018

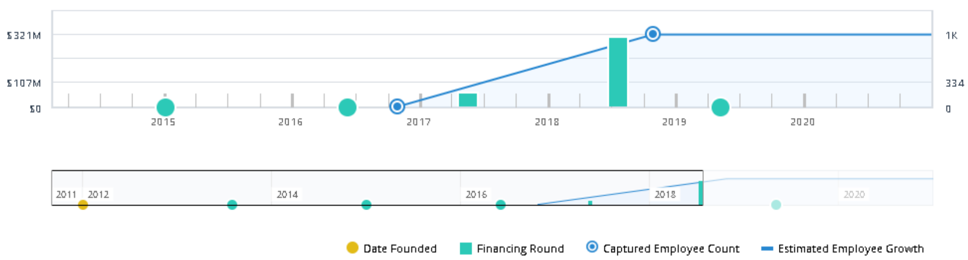
Last Deal Details
Undisclosed
Later Stage VC 06-May-2019

Total Raised to Date
$355.16M
As of 06-May-2019

Edit Highlights

Timeline

Round & Amount



General Information

Description
Provider and developer of artificial intelligence technology used in the fields of smart cities, smart medical, and smart commerce. The company is engaged in the research of computer vision, image and video intelligent understanding, distributed system and big data application, it offers traffic management software, medical diagnostic technology and intelligent hardware, enabling companies to apply AI technology in their products.

Most Recent Financing Status (as of 13-Feb-2020)
The company raised an undisclosed amount of venture funding from [redacted]
Previously, the company raised $300 million of Series C+ venture funding from [redacted]

Website	[redacted]		
Entity Types	Private Company Acquirer	Financing Status	Venture Capital-Backed
		Year Founded	2012
Legal Name	[redacted]	Universe	Venture Capital
Business Status	Generating Revenue	Employees	1,000
Ownership Status	Privately Held (backing)		View Employee History

Industries & Verticals

Primary Industry
Business/Productivity Software

Verticals
Artificial Intelligence & Machi...
Big Data
Digital Health
TMT

What PitchBook Analysts Say — View More Analyst Insights

"Both incumbents and startups are developing new hardware. While Google is putting their custom tensor processing units (TPUs) to use for many recent breakthroughs, independent leaders such as Cerebras and Graphcore have raised significant capital and developed other novel designs to cater to AI & ML applications."

| 10-Dec-2019 | Cameron Stanfill | Artificial Intelligence & Machine Learning +3

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Phone: [redacted]

Alternate Offices (4)
Beijing
[redacted]
China
Phone: [redacted]

Figure A.3: Example of AI firm record from *Pitchbook* (excerpt).

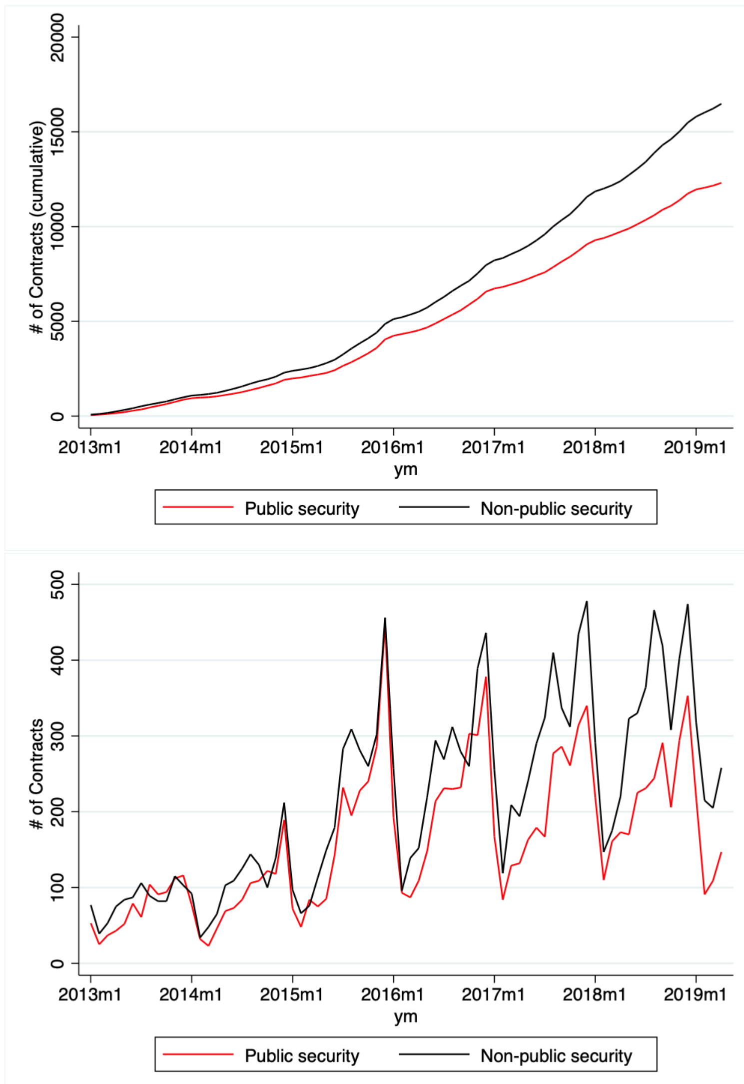


Figure A.4: Cumulative number of public security and non-public security contracts (top panel), and the flow of new contracts signed in each month (bottom panel).

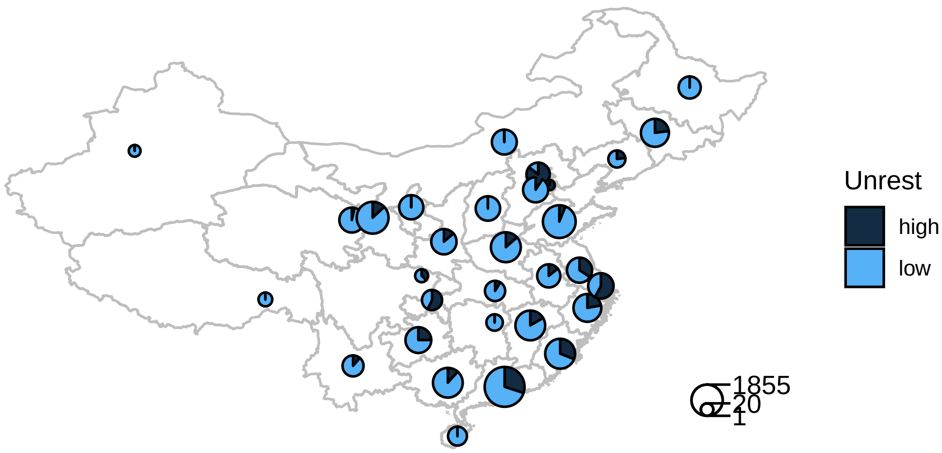


Figure A.5: Each circle represents a province in our dataset that has at least one public security AI contract that is some AI firm's first government contract. Circle size indicates the number of public security AI contracts awarded to a prefecture in the province (larger circles indicate more contracts, log scale), where prefecture-level contracts are weighted by the number of prefectures in the province. Circle shading indicates the fraction of first AI contracts that were procured during high or low unrest periods, where the within-prefecture variation comes from changes in the number of unrest events in a prefecture over time (a larger fraction of dark shading indicates a larger fraction of prefecture contracts procured during high unrest periods).

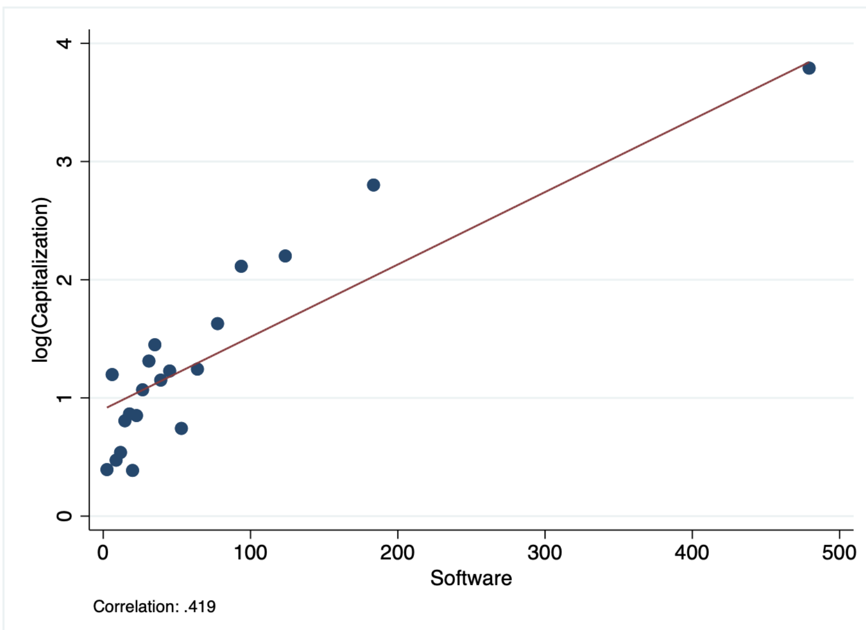
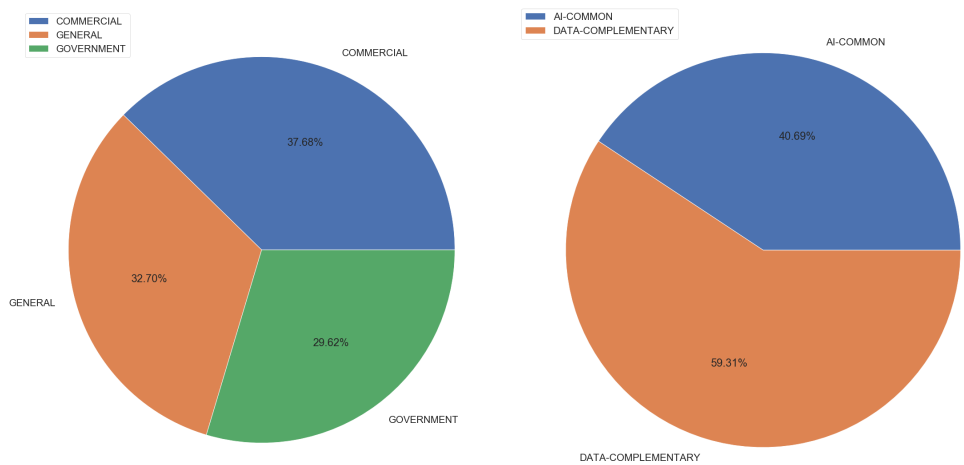


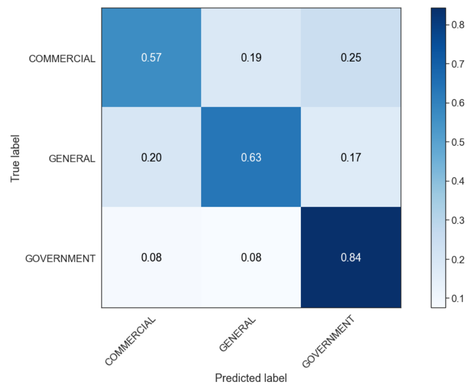
Figure A.6: Binscatter plot at the firm level of log(firm capitalization) and amount of software produced.



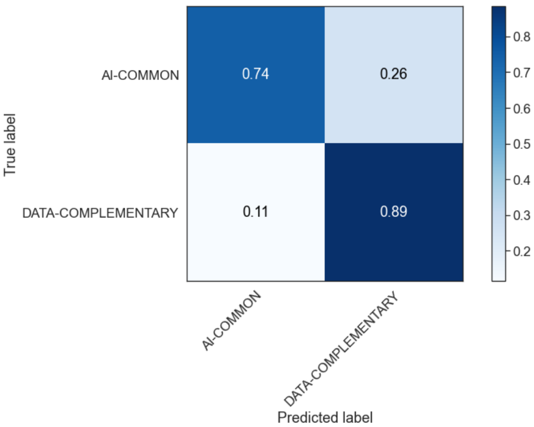
(a) Customers

(b) Function

Figure A.7: Summary statistics of categorization outcomes for software categorizations based on Recurrent Neural Network with Long Short-Term Memory algorithm. Left panel shows categorization by customers; right panel shows categorization by function.

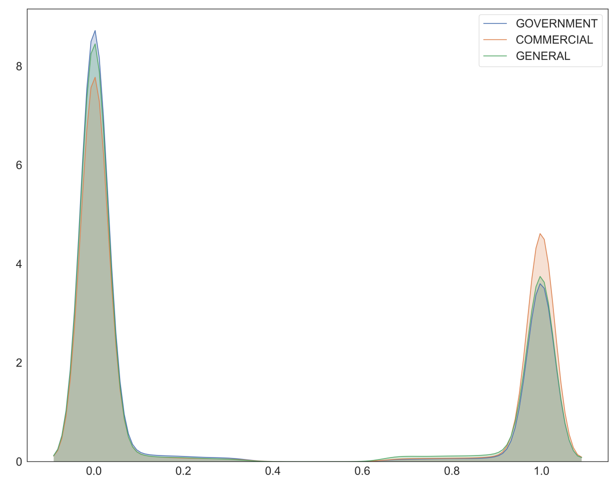


(a) Customers

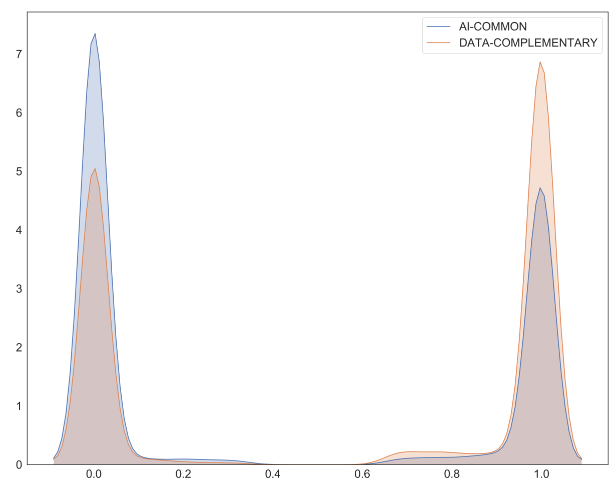


(b) Functions

Figure A.8: Confusion matrix of categorization outcomes for software categorizations. True labels are based on training set constructed by human categozations (performed by two individuals). Predicted labels are outputs based on Recurrent Neural Network with Long Short-Term Memory algorithm. Left panel shows categorization by customers; right panel shows categorization by function.



(a) Customers



(b) Function

Figure A.9: Probability density plots of software categorizations based on Recurrent Neural Network with Long Short-Term Memory algorithm. Top panel shows categorization by customers; bottom panel shows categorization by function.

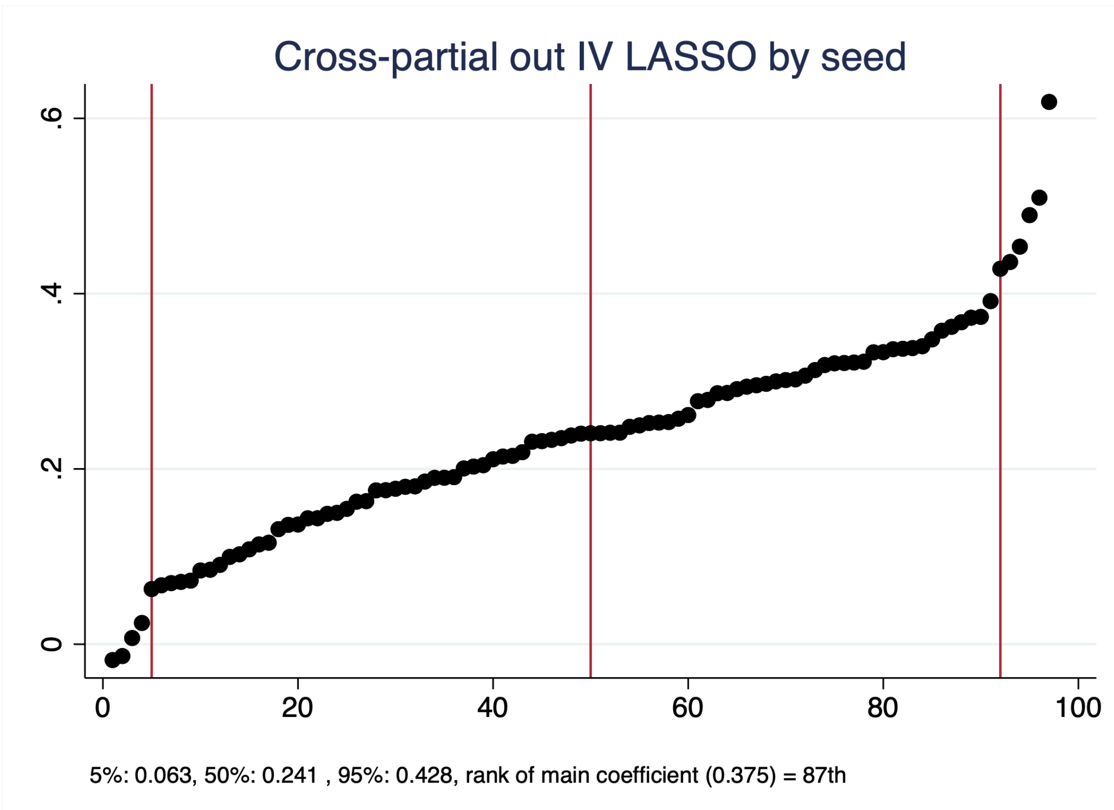


Figure A.10: Effect of unrest events on facial recognition AI procurement, varying LASSO seed from 1-100. The baseline specification uses seed = 1.

Government surveillance

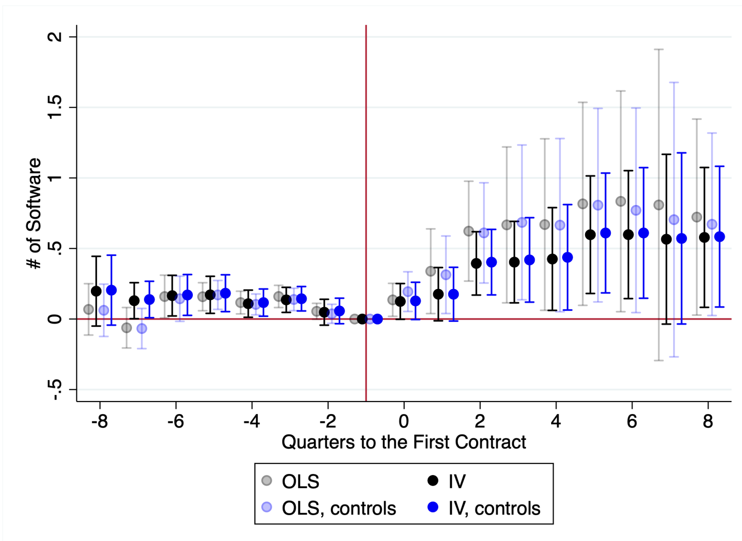


Figure A.11: Differential effects of politically motivated contracts on software developed for government surveillance applications by firms that receive public security contracts versus non-public security ones, relative to the time of receiving the initial contract. All panels restrict firms to those that receive contracts in prefectures experiencing above-median political unrest (or predicted unrest) in the previous quarter, and control for firm and time period fixed effects. Black lines/markers show the total effect over time for firms. Blue lines/markers add controls for an inverse covariance weighted index of firm productivity containing contract size and company size. Dark lines/markers use LASSO selected weather variables to instrument for unrest.

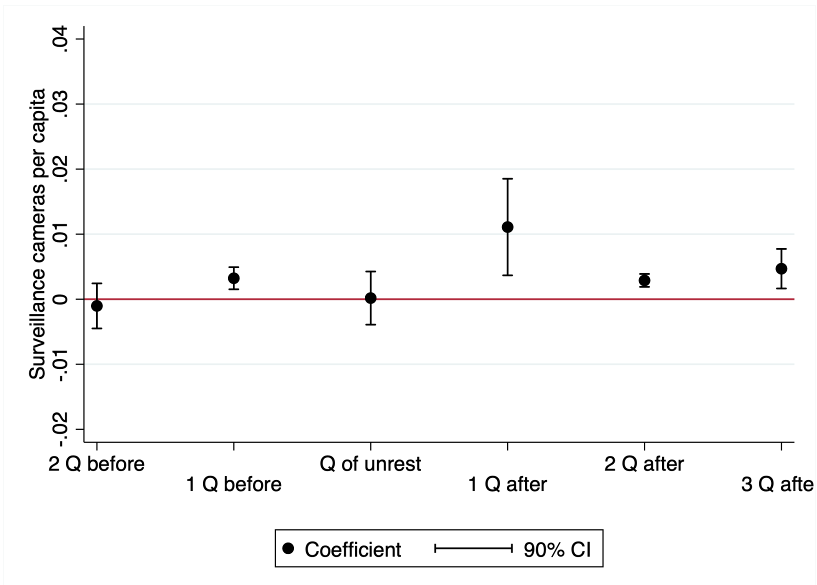


Figure A.12: Surveillance cameras per capita relative to the quarter of political unrest. This figure plots the estimated effects of leads and lags of prefecture political unrest on prefecture surveillance camera procurement per capita from a regression that also includes quarter and prefecture fixed effects. The outcome (camera procurement) and explanatory variables of interest (unrest events) are standardized to mean = 0, variance = 1.

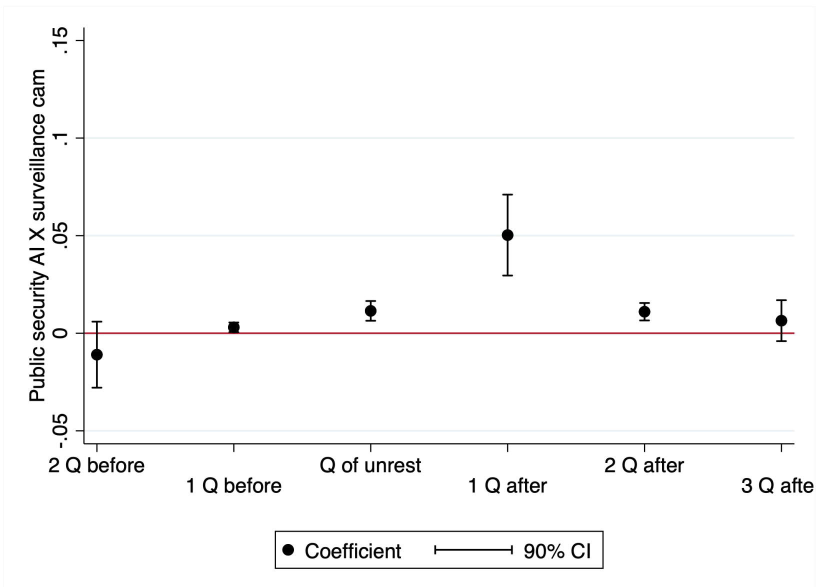


Figure A.13: Public security AI investments interacted with surveillance cameras per capita relative to the quarter of political unrest. This figure plots the estimated effects of leads and lags of prefecture political unrest on prefecture public security AI investment interacted with surveillance camera procurement per capita from a regression that also includes quarter and prefecture fixed effects. The outcome (AI $\times$ camera procurement) and explanatory variables of interest (unrest events) are standardized to mean = 0, variance = 1.

Data-complementary

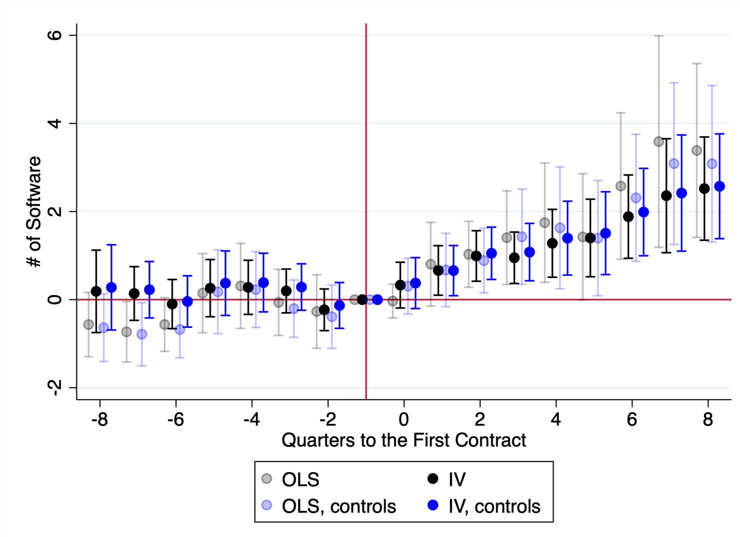
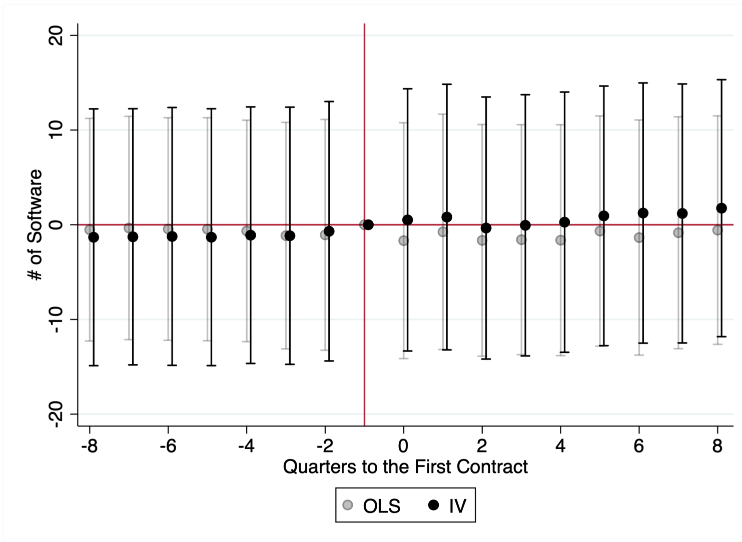


Figure A.14: Differential effects of politically motivated contracts on data-complementary software developed by firms that receive public security contracts versus non-public security ones, relative to the time of receiving the initial contract. All panels restrict firms to those that receive contracts in prefectures experiencing above-median political unrest (or predicted unrest) in the previous quarter, and control for firm and time period fixed effects. Black lines/markers show the total effect over time for firms. Blue lines/markers add controls for an inverse covariance weighted index of firm productivity containing contract size and company size. Dark lines/markers use LASSO selected weather variables to instrument for unrest.

Panel A: Commercial software



Panel B: Commercial surveillance software

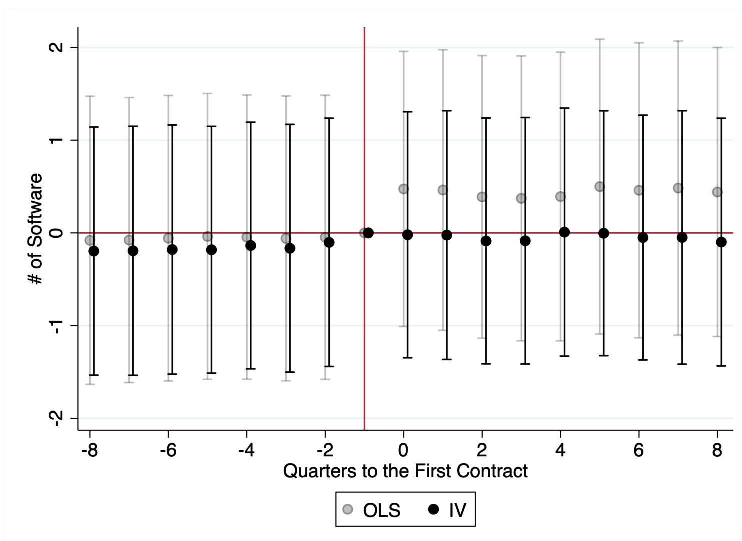
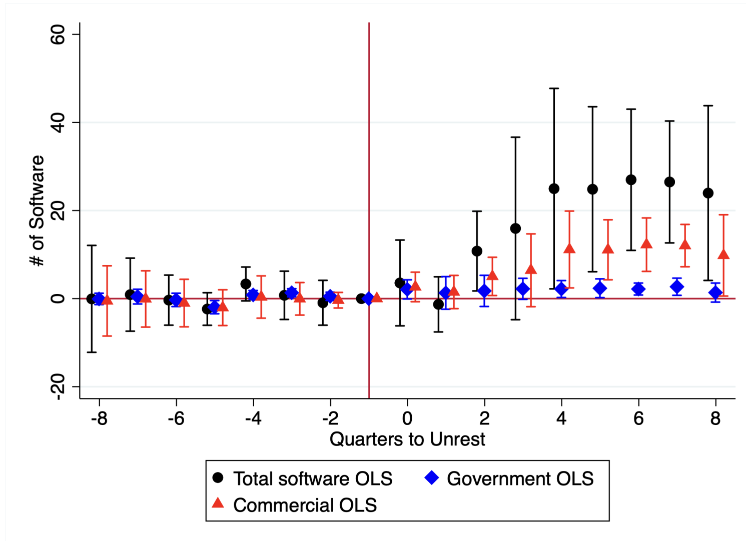


Figure A.15: This figure displays differential software development by firms that receive politically motivated public security contracts (issued in prefectures with above median unrest) versus politically neutral public security ones (issued in prefectures with below median unrest), relative to the time of receiving the initial contract. Total software is plotted in black. In Panel A, commercial software is plotted in blue. In Panel B, commercial surveillance software is plotted in blue. All panels control for firm and time period fixed effects. Dark lines/markers use weather to instrument for unrest.

Panel A: Firm HQ in localities that experience political unrest



Panel B: Firm HQ in localities where AI firms receiving politically motivated contracts also have HQ

Panel C: Firms that are part of a mother firm with other subsidiaries that received politically motivated contracts

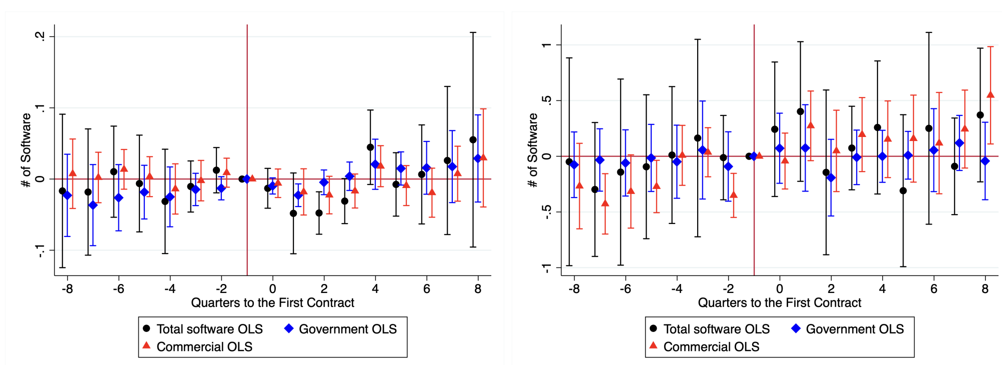


Figure A.16: This figure displays the full set of coefficients and standard errors from Table 7. AI firms who are proximate to other firms that receive politically motivated public security contracts. Firms that receive politically motivated public security contracts are defined as: firms that are headquartered in prefectures that experience above median amounts of political unrest in Panel A, firms headquartered in prefectures where other AI firms that have received politically motivated contracts are headquartered in Panel B, or firms that belong to mother firms whose other subsidiaries have received politically motivated contracts in Panel C. The figure shows the difference in total software production between firms that earn politically motivated (public security) contracts versus firms that do not earn a contract. All subfigures control for time period fixed effects and firm fixed effects. Panels B and C additionally control for contract fixed effect. Black lines/dots show the total effect over time for firms, the blue lines/diamonds show the effect for government software, and the red lines/triangles show the effect for commercial software.

	Rank	Algorithm	Submission date	VISA Photos	MUGSHOT Photos	BORDER Photos	WILD Photos
	1	cloudwalk-mt-005	29/3/2022	0.0009[1]	0.0025[24]	0.0305[68]	0.8895[201]
	2	sensetime-007	17/6/2022	0.0022[14]	0.0021[2]	0.0300[21]	0.0423[2]
	3	megvii-005	28/3/2022	0.0015[4]	0.0026[33]	0.0313[114]	0.0663[37]
	4	sensetime-006	28/12/2021	0.0024[20]	0.0021[1]	0.0299[6]	0.0475[4]
	5	kakao-008	12/5/2022	0.0018[8]	0.0023[4]	0.0447[261]	0.0417[1]
	6	samsungsds-001	18/4/2022	0.0026[26]	0.0023[7]	0.0302[32]	0.2598[164]
	7	vocord-010	20/12/2021	0.0031[34]	0.0036[101]	0.0301[31]	0.0519[11]
	8	ntechlab-012	20/1/2022	0.0016[5]	0.0023[9]	0.0302[39]	0.0501[8]
	9	s1-005	17/6/2022	0.0036[46]	0.0025[29]	0.0384[225]	0.0491[6]
	10	hyperverge-003	11/4/2022	0.0030[33]	0.0025[22]	0.0302[41]	0.0502[9]

Figure A.17: Face Recognition Vendor Test (FRVT) 2020 ranking of top facial recognition algorithms. Source: *National Institute of Standards and Technology (NIST)*.

Table A.1: Top predicted words from LSTM model — non-binary categorization of software

Panel A: Customer type

Government			Commercial			General		
Chinese	English	Freq. (%)	Chinese	English	Freq. (%)	Chinese	English	Freq. (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
交通	Traffic	.603	手机	Mobile Phone	.821	视觉	Vision	.474
威视	Nuctech	.382	APP	App	.645	学习	Learning	.378
海康	Haikang	.369	IOS	IOS	.438	腾讯	Tencent	.340
平安	Safety	.351	iOS	iOS	.430	三维	3D	.312
海信	Hisense	.318	企业	Enterprise	.331	识别系统	Recognition System	.301
城市	City	.311	金蝶	Kingdee	.327	算法	Algorithm	.270
金融	Finance	.296	电子	Electronics	.307	计算	Computing	.252
安防	Safety	.281	健康	Health	.212	深度	Depth	.225
数字	Numbers	.272	自助	Self-Help	.209	无人机	Drone	.212
中心	Center	.269	手机游戏	Mobile Game	.201	实时	Real-time	.209
公交	Public Transport	.216	助手	Assistance	.196	认证	Certification	.207
社区	Community	.207	支付	Pay	.191	处理	Processing	.196
调度	Scheduling	.200	后台	Backstage	.189	引擎	Engine	.194
中控	Central Control	.191	门禁	Access Control	.176	技术	Technique	.187
人像	Portrait	.163	人工智能	AI	.174	分布式	Distributed	.183
指挥	Command	.161	车载	Vehicle	.174	仿真	Simulation	.179
辅助	Auxilary	.159	智能家居	Smart Appliance	.169	网易	Netease	.173
摄像机	Camera	.158	工业	Industry	.169	工具软件	Tool Software	.172
万达	Wanda	.148	DHC	DHC	.168	程序	Program	.170
高速公路	Highway	.148	营销	Marketing	.161	互动	Interactive	.166

Panel B: Function type

AI-Common			Data-Complementary			AI-Video		
Chinese	English	Freq. (%)	Chinese	English	Freq. (%)	Chinese	English	Freq. (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
指纹	Fingerprint	.342	存储	Storage	.206	人脸	Face	1.104
训练	Training	.203	可视化	Visualization	.167	深度	Depth	.321
管家	Housekeeper	.201	一体化	Integration	.164	抓拍	Snapshot	.310
文本	Text	.151	分布式	Distributed	.162	商汤	SenseTime	.287
高速公路	Highway	.150	仿真	Simulation	.157	考勤	Attendance	.258
虹膜	Iris	.147	医学影像	Medical Imaging	.148	科达	Kedacom	.258
汽车	Car	.143	通用	General	.144	跟踪	Track	.249
海尔	Haier	.137	集成	Integrated	.141	全景	Panoramic	.224
WPS	WPS	.134	数据管理	Data Management	.136	广电	Broadcastt	.209
翻译	Translate	.126	宇视	UTV	.136	目标	Target/Objective	.189
推荐	Recommend	.124	管控	Manage	.126	车牌	License Plate	.189
图片	Image	.119	高速	High Speed	.126	特征	Feature	.184
测量	Test	.116	媒体	Media/Medium	.125	铂亚	Platinum	.175
征信	Credit	.111	手机软件	Phone Software	.125	预警	Warning	.166
指纹识别	Fingerprint Recognition	.106	设计	Design	.117	运通	American Express	.163
作业	Operation	.106	接口	Interface	.117	指挥	Command	.158
微信	WeChat	.105	开发	Development	.116	统计	Statistics	.149
评估	Assessment	.105	服务器	Server	.116	安居	Safety	.146
灵云	AIcloud	.102	处理软件	Processing Software	.113	SDK	SDK	.141
活体	Living Body	.098	传输	Transmission	.111	布控	Deploymentt	.141

Table A.2: Effect of different kinds of unrest on AI procurement

	Public security AI procurement			
	(1)	(2)	(3)	(4)
Panel A.1: OLS — protests				
Unrest events$_{t-1}$	0.153***	0.152***	0.153***	0.153***
	(0.016)	(0.016)	(0.016)	(0.016)
Panel A.2: IV — protests				
Unrest events$_{t-1}$	0.287***	0.290***	0.287***	0.295***
	(0.058)	(0.057)	(0.058)	(0.055)
Panel B.1: OLS — demands				
Unrest events$_{t-1}$	0.120***	0.117***	0.119***	0.119***
	(0.041)	(0.042)	(0.041)	(0.040)
Panel B.2: IV — demands				
Unrest events$_{t-1}$	0.307***	0.304***	0.307***	0.304***
	(0.078)	(0.077)	(0.078)	(0.077)
Panel C.1: OLS — threats				
Unrest events$_{t-1}$	0.197***	0.192***	0.197***	0.195***
	(0.051)	(0.054)	(0.052)	(0.051)
Panel C.2: IV — threats				
Unrest events$_{t-1}$	0.362***	0.211**	0.362***	0.211**
	(0.086)	(0.095)	(0.086)	(0.095)
GDP $\times$ quarter	Yes	No	No	Yes
Log population $\times$ quarter	No	Yes	No	Yes
Gov. revenue $\times$ quarter	No	No	Yes	Yes

Notes: This table follows Table 2 and presents regressions at the prefecture-quarter level. The outcome is the number of public security facial recognition AI contracts procured by the local government, standardized to mean = 0 and variance = 1. The explanatory variable of interest in Panel A restricts unrest to only protests, Panel B restricts unrest events to only demands, and Panel C restricts unrest events to only threats, all of which are standardized. Column 1 controls for prefecture GDP x quarter effects, column 2 controls for log prefecture population x quarter effects, column 3 controls for prefectural government tax revenue x quarter effects, and column 4 includes all controls. Panels A.1, B.1, and C.1 present OLS regression estimates. Panels A.2, B.2, and C.2 present a cross-fit partialing-out LASSO IV specification: we instrument for daily unrest events using weather variables interacted with themselves and an indicator for whether an unrest event occurred elsewhere in China on the day (variables are selected by LASSO), and aggregate to the quarter level. All specifications include prefecture and quarter fixed effects. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.3: First stage - LASSO selected variables and weights

Variable	Cross-fitting fold #									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Thunder X unrest elsewhere	.0394	.0437	.0223		.0077	.0364		.0424	.0314	.0222
Thunder X visibility	.0002	.0010	.0048							.0222
Precipitation X pressure X unrest elsewhere			.0167	.0223			.0159			.0091
Thunder X pressure X unrest elsewhere				.0032			.0034	.0002		
Pressure X visibility X unrest elsewhere				.0026	.0019		.0034		.0053	
Pressure X pressure X unrest elsewhere				.0011	.0235					
Snow X pressure X unrest elsewhere					.0015	.0005				
Fog X visibility							.0023			
Fog X visibility X unrest elsewhere									.0019	

Notes: This table displays the weather variables selected by LASSO alongside the weights placed on each variable by the LASSO regression. Since a cross-fit partialing-out LASSO IV is used, results for each of the ten folds are displayed. Thunder, snow, and fog are indicators for the presence of each weather condition. Precipitation is measured in inches, visibility in miles, and pressure in millibars (mean station pressure). Unrest elsewhere is an indicator for an unrest event occurring elsewhere in China on the day. Empty cells indicate omitted weather variables.

Table A.4: Effect of public security AI on police hiring

	Police hires	
	(1)	(2)
Panel A: Police hires		
Public security AI_{t-1}	-0.072*	-0.072*
	(0.039)	(0.039)
Panel B: % office police		
Public security events_{t-1}	0.047**	0.044**
	(0.020)	(0.020)
Prefecture revenue	Yes	Yes
Prefecture population	No	Yes

Notes: This table presents regressions at the prefecture-year level, with police hiring data one year after AI procurement. The outcome in Panel A is the standardized number of new police hired, the outcome in Panel B is the share of desk jobs among new police hires. In both panels, the explanatory variable of interest is the standardized number of public security AI contracts, topcoded at the 5% threshold. Column 1 controls for local prefecture government revenue in the given year, and column 2 adds the control for prefecture population. All specifications include prefecture and year fixed effects. Standard errors are robust. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.5: Effects of local politicians' incentives on current unrest

	Standardized number of events			
	(1)	(2)	(3)	(4)
Panel A: Weather shock and local politician career incentive on local unrest				
Fine weather	0.4526***	0.4547***	0.4527***	0.4550***
	(0.0143)	(0.0142)	(0.0145)	(0.0142)
Politician incentive	0.0005	0.0006	0.0006	0.0005
	(0.0009)	(0.0010)	(0.0008)	(0.0010)
Fine weather $\times$ politician incentive	0.0002	0.0006	0.0003	0.0007
	(0.0074)	(0.0074)	(0.0072)	(0.0073)
GDP $\times$ quarter	Yes	No	No	Yes
Log population $\times$ quarter	No	Yes	No	Yes
Gov. revenue $\times$ quarter	No	No	Yes	Yes

Notes: This table follows the specification in Table 4 columns 1-4, and presents regressions at the prefecture-quarter level. Fine weather (LASSO) is the standardized number of predicted events from the fine weather LASSO variables interacted with whether there was an event elsewhere in China on the day. Local unrest in prior periods is also standardized; Panel A constructs an index of the career concerns of the prefecture leader using their age and political hierarchy level, following Wang et al. (2020). Prefecture and quarter fixed effects are included. Column 1 adds controls for prefecture GDP $\times$ quarter fixed effects, column 2 adds controls for log prefecture population $\times$ quarter fixed effects, column 3 adds controls for prefectural government revenue $\times$ quarter fixed effects, and column 4 adds all prior controls. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.6: Total effect of politically-motivated public security contracts on total software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	3.402	4.756	0.274	1.744	2.414	-0.230
	(3.189)	(4.164)	(2.038)	(1.771)	(2.132)	(1.492)
7 quarters before contract	2.342	3.649	-0.178	1.279	1.894	-0.347
	(2.823)	(3.882)	(1.825)	(1.469)	(1.777)	(1.190)
6 quarters before contract	1.759	2.998	-0.295	1.047	1.465	-0.308
	(2.421)	(3.643)	(1.696)	(1.343)	(1.603)	(1.147)
5 quarters before contract	1.136	2.647	-0.476	0.365	0.782	-0.762
	(1.247)	(2.295)	(0.878)	(0.755)	(0.961)	(0.648)
4 quarters before contract	0.721	2.288	-0.362	0.124	0.542	-0.713
	(1.101)	(2.459)	(0.878)	(0.705)	(0.928)	(0.629)
3 quarters before contract	-0.115	1.528	-0.733	-0.106	0.277	-0.647
	(0.730)	(2.099)	(0.725)	(0.580)	(0.729)	(0.561)
2 quarters before contract	-1.174*	0.505	-1.510**	-0.837*	-0.428	-1.095**
	(0.686)	(1.810)	(0.652)	(0.424)	(0.557)	(0.423)
Receiving 1st contract	1.044	1.434	1.101	0.563	0.648	0.831*
	(2.077)	(2.396)	(1.880)	(0.480)	(0.492)	(0.438)
1 quarter after contract	2.570	3.880**	2.707	1.878	1.968*	2.203**
	(2.531)	(1.878)	(2.062)	(1.221)	(1.153)	(1.063)
2 quarters after contract	3.180	4.789**	3.680	2.633*	3.113**	3.261***
	(2.787)	(2.093)	(2.243)	(1.401)	(1.345)	(1.235)
3 quarters after contract	4.037	5.702**	4.783*	3.185*	3.704**	3.993***
	(3.357)	(2.782)	(2.566)	(1.678)	(1.708)	(1.416)
4 quarters after contract	5.659	7.338**	6.604*	4.074*	4.627**	5.138***
	(4.260)	(3.577)	(3.395)	(2.097)	(2.115)	(1.813)
5 quarters after contract	6.022	7.772**	7.372**	5.278**	5.785***	6.416***
	(4.285)	(3.254)	(3.285)	(2.198)	(2.178)	(1.857)
6 quarters after contract	7.204	8.565**	8.943**	6.308**	6.721***	7.599***
	(4.916)	(3.476)	(3.678)	(2.409)	(2.417)	(2.054)
7 quarters after contract	8.916	10.178**	11.092**	7.708**	8.108***	9.324***
	(6.147)	(4.052)	(4.797)	(2.929)	(2.913)	(2.560)
8 quarters after contract	10.746***	11.245***	13.149***	9.258***	9.673***	11.114***
	(3.917)	(3.313)	(3.059)	(2.072)	(2.071)	(1.926)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in total software production between firms that earn politically motivated (public security) contracts versus firms that do not earn a contract. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.7: Total effect of politically-motivated public security contracts on government software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	1.523	1.833	0.408	0.660	0.744	-0.109
	(1.309)	(1.483)	(0.967)	(0.695)	(0.729)	(0.679)
7 quarters before contract	0.928	1.238	0.049	0.363	0.445	-0.282
	(1.082)	(1.312)	(0.759)	(0.526)	(0.561)	(0.494)
6 quarters before contract	0.814	1.107	0.103	0.329	0.380	-0.203
	(0.992)	(1.255)	(0.755)	(0.481)	(0.511)	(0.455)
5 quarters before contract	0.620	0.953	0.064	0.188	0.242	-0.262
	(0.499)	(0.719)	(0.396)	(0.370)	(0.386)	(0.368)
4 quarters before contract	0.360	0.724	-0.018	0.017	0.068	-0.311
	(0.416)	(0.699)	(0.335)	(0.336)	(0.358)	(0.330)
3 quarters before contract	0.292	0.660	0.025	-0.004	0.044	-0.226
	(0.284)	(0.563)	(0.269)	(0.212)	(0.226)	(0.208)
2 quarters before contract	-0.378*	0.004	-0.508**	-0.253	-0.202	-0.377*
	(0.212)	(0.471)	(0.196)	(0.228)	(0.236)	(0.222)
Receiving 1st contract	0.388	0.468	0.402	0.302*	0.307*	0.356**
	(0.374)	(0.390)	(0.349)	(0.175)	(0.171)	(0.163)
1 quarter after contract	1.081*	1.371***	1.061**	0.724**	0.736**	0.776***
	(0.571)	(0.488)	(0.493)	(0.282)	(0.279)	(0.258)
2 quarters after contract	1.271**	1.646***	1.386***	1.221***	1.275***	1.364***
	(0.594)	(0.479)	(0.492)	(0.301)	(0.295)	(0.275)
3 quarters after contract	1.634*	2.023**	1.793**	1.393***	1.469***	1.626***
	(0.944)	(0.814)	(0.793)	(0.417)	(0.422)	(0.365)
4 quarters after contract	1.972	2.345**	2.276**	1.691***	1.763***	2.027***
	(1.177)	(1.081)	(1.019)	(0.557)	(0.562)	(0.505)
5 quarters after contract	2.083	2.462**	2.476**	2.071***	2.143***	2.438***
	(1.340)	(1.163)	(1.144)	(0.656)	(0.661)	(0.623)
6 quarters after contract	2.443	2.769*	3.009**	2.352***	2.413***	2.782***
	(1.636)	(1.385)	(1.452)	(0.747)	(0.754)	(0.742)
7 quarters after contract	3.143	3.403**	3.815**	2.799***	2.846***	3.341***
	(2.067)	(1.653)	(1.772)	(0.941)	(0.944)	(0.931)
8 quarters after contract	3.441**	3.538**	4.191***	3.115***	3.171***	3.755***
	(1.497)	(1.361)	(1.363)	(0.900)	(0.898)	(0.943)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in government software production between firms that earn politically motivated (public security) contracts versus firms that do not earn a contract. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.8: Total effect of politically-motivated public security contracts on commercial software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	1.496	2.256	0.148	0.492	0.798	-0.225
	(1.599)	(2.109)	(1.031)	(0.741)	(0.944)	(0.491)
7 quarters before contract	0.936	1.668	-0.121	0.356	0.632	-0.218
	(1.330)	(1.949)	(0.858)	(0.618)	(0.763)	(0.417)
6 quarters before contract	0.689	1.388	-0.173	0.265	0.443	-0.218
	(1.129)	(1.867)	(0.769)	(0.541)	(0.674)	(0.385)
5 quarters before contract	0.502	1.388	-0.208	0.222	0.418	-0.197
	(0.566)	(1.218)	(0.305)	(0.327)	(0.423)	(0.230)
4 quarters before contract	0.433	1.346	-0.049	0.168	0.371	-0.146
	(0.468)	(1.360)	(0.294)	(0.276)	(0.395)	(0.197)
3 quarters before contract	-0.035	0.893	-0.298	0.043	0.204	-0.155
	(0.288)	(1.222)	(0.188)	(0.209)	(0.292)	(0.178)
2 quarters before contract	-0.361	0.613	-0.516***	-0.181	-0.005	-0.302**
	(0.219)	(1.050)	(0.183)	(0.161)	(0.239)	(0.146)
Receiving 1st contract	0.560*	0.758	0.557**	0.425*	0.461	0.487**
	(0.326)	(0.716)	(0.248)	(0.220)	(0.289)	(0.190)
1 quarter after contract	1.096	1.761	1.088	0.945	0.970	1.004
	(1.471)	(1.096)	(1.232)	(0.827)	(0.795)	(0.723)
2 quarters after contract	1.194	2.044*	1.394	1.046	1.268	1.223
	(1.544)	(1.151)	(1.275)	(0.918)	(0.917)	(0.787)
3 quarters after contract	1.464	2.383	1.725	1.217	1.414	1.458
	(1.908)	(1.680)	(1.524)	(1.048)	(1.085)	(0.878)
4 quarters after contract	2.132	3.095	2.438	1.588	1.835	1.938*
	(2.357)	(1.937)	(1.891)	(1.286)	(1.326)	(1.094)
5 quarters after contract	2.177	3.208*	2.685	1.929	2.155	2.325**
	(2.276)	(1.741)	(1.731)	(1.339)	(1.356)	(1.088)
6 quarters after contract	2.673	3.449*	3.398*	2.347*	2.527*	2.813**
	(2.537)	(1.741)	(1.925)	(1.406)	(1.433)	(1.137)
7 quarters after contract	3.567	4.263**	4.434*	3.020*	3.191*	3.571**
	(3.181)	(1.956)	(2.498)	(1.703)	(1.700)	(1.406)
8 quarters after contract	5.090**	5.318***	5.976***	3.728***	3.903***	4.374***
	(2.293)	(1.906)	(1.794)	(1.161)	(1.175)	(0.958)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in commercial software production between firms that earn politically motivated (public security) contracts versus firms that do not earn a contract. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.9: Differential effect of politically-motivated public security contracts on total software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	4.898	3.578	0.344	1.210	0.077	-1.309
	(3.216)	(2.346)	(1.144)	(1.305)	(1.168)	(0.824)
7 quarters before contract	4.060	2.917	0.195	0.924	0.121	-1.230*
	(2.847)	(2.096)	(1.039)	(1.116)	(1.020)	(0.626)
6 quarters before contract	3.013	2.646	-0.053	1.111	0.691	-0.618
	(2.186)	(1.954)	(0.783)	(0.926)	(0.903)	(0.513)
5 quarters before contract	1.280	0.927	-1.234***	0.217	-0.516	-1.192***
	(1.249)	(1.006)	(0.450)	(0.521)	(0.496)	(0.431)
4 quarters before contract	0.704	0.598	-1.123***	-0.135	-0.661	-1.229***
	(0.967)	(0.852)	(0.279)	(0.448)	(0.482)	(0.390)
3 quarters before contract	0.463	0.318	-0.731***	-0.248	-0.660*	-0.938***
	(0.643)	(0.542)	(0.263)	(0.344)	(0.390)	(0.339)
2 quarters before contract	-0.327	-0.280	-0.801***	-0.148	-0.151	-0.482**
	(0.351)	(0.393)	(0.179)	(0.173)	(0.269)	(0.185)
Receiving 1st contract	0.301	0.686	0.658	0.110	-0.005	0.410
	(0.430)	(0.452)	(0.407)	(0.339)	(0.343)	(0.314)
1 quarter after contract	-1.167	1.202*	-0.024	-0.729	0.165	0.044
	(1.337)	(0.680)	(1.029)	(0.839)	(0.435)	(0.616)
2 quarters after contract	-1.557	1.358	0.518	-0.589	0.408	0.796
	(1.629)	(0.836)	(1.110)	(1.018)	(0.552)	(0.721)
3 quarters after contract	-1.665	1.835**	0.414	-0.481	0.947	0.930
	(2.026)	(0.835)	(1.175)	(1.177)	(0.606)	(0.758)
4 quarters after contract	-1.470	2.955**	1.108	-0.152	1.619**	1.499*
	(2.318)	(1.103)	(1.358)	(1.290)	(0.706)	(0.838)
5 quarters after contract	-1.591	3.401**	1.954	-0.005	2.091**	2.178**
	(2.509)	(1.334)	(1.273)	(1.384)	(0.915)	(0.882)
6 quarters after contract	-1.249	5.023***	3.154**	0.663	3.348***	3.163***
	(3.030)	(1.787)	(1.409)	(1.553)	(1.170)	(1.052)
7 quarters after contract	-1.574	4.357**	3.760**	0.851	3.639***	3.987***
	(3.520)	(1.729)	(1.505)	(1.773)	(1.193)	(1.210)
8 quarters after contract	0.977	4.683**	6.396***	1.864*	4.039***	5.450***
	(1.521)	(1.948)	(1.747)	(1.024)	(1.303)	(1.283)
8 quarters before contract × public security	-1.690	-1.796	-1.709	0.574	0.976	0.274
	(1.220)	(1.527)	(1.124)	(1.136)	(1.347)	(1.201)
7 quarters before contract × public security	-1.896	-1.757	-1.668*	0.372	0.605	0.238
	(1.200)	(1.336)	(0.960)	(0.893)	(0.937)	(0.927)
6 quarters before contract × public security	-1.420	-1.760	-1.312	-0.036	-0.054	-0.225
	(0.968)	(1.388)	(0.866)	(0.922)	(0.930)	(0.982)
5 quarters before contract × public security	-0.296	-0.772	-0.114	0.177	0.737	-0.052
	(0.615)	(1.302)	(0.708)	(0.552)	(1.048)	(0.529)
4 quarters before contract × public security	-0.115	-0.770	0.168	0.267	0.526	0.128
	(0.596)	(1.224)	(0.785)	(0.541)	(0.975)	(0.519)
3 quarters before contract × public security	-0.608	-0.896	-0.330	0.180	0.589	0.059
	(0.527)	(0.972)	(0.682)	(0.483)	(0.839)	(0.499)
2 quarters before contract × public security	-1.009**	-0.846	-0.937*	-0.642	-0.527	-0.715*
	(0.454)	(1.127)	(0.532)	(0.405)	(0.796)	(0.411)
Receiving 1st contract × public security	0.570	0.060	0.381	0.536	0.595	0.624**
	(0.439)	(0.810)	(0.384)	(0.335)	(0.414)	(0.253)
1 quarter after contract × public security	3.647**	0.818	2.709**	2.670***	1.534**	2.344***

	(1.661)	(1.263)	(1.246)	(0.960)	(0.610)	(0.800)
2 quarters after contract × public security	4.782***	1.861	3.374**	3.363***	2.429***	2.837***
	(1.759)	(1.736)	(1.334)	(1.031)	(0.761)	(0.944)
3 quarters after contract × public security	5.594**	1.689	4.568***	3.746***	2.345**	3.450***
	(2.264)	(1.824)	(1.569)	(1.240)	(0.911)	(1.033)
4 quarters after contract × public security	7.070**	1.673	5.834**	4.228**	2.190*	4.103***
	(3.118)	(2.569)	(2.353)	(1.688)	(1.147)	(1.446)
5 quarters after contract × public security	7.565**	1.218	6.003**	5.412***	2.791**	4.661***
	(3.000)	(2.757)	(2.233)	(1.767)	(1.364)	(1.450)
6 quarters after contract × public security	8.225**	1.234	6.504**	5.749***	2.714*	4.914***
	(3.363)	(3.027)	(2.580)	(1.892)	(1.484)	(1.625)
7 quarters after contract × public security	10.458**	3.269	8.395**	6.929***	3.424**	5.858***
	(4.554)	(3.151)	(3.687)	(2.358)	(1.504)	(2.029)
8 quarters after contract × public security	9.746***	3.908	7.816***	7.512***	4.110**	6.396***
	(3.246)	(3.891)	(2.390)	(1.869)	(1.623)	(1.562)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in software production between firms that earn politically motivated (public security) contracts versus non-politically motivated contracts. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.10: Differential effect of politically-motivated public security contracts on government software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	1.686	0.957	0.064	0.354	-0.036	-0.598
	(1.056)	(0.701)	(0.511)	(0.557)	(0.728)	(0.521)
7 quarters before contract	1.378	0.754	-0.011	0.092	-0.255	-0.702*
	(0.976)	(0.618)	(0.472)	(0.410)	(0.521)	(0.379)
6 quarters before contract	0.863	0.595	-0.250	0.114	-0.173	-0.548*
	(0.712)	(0.598)	(0.352)	(0.349)	(0.438)	(0.306)
5 quarters before contract	0.339	0.254	-0.554**	-0.111	-0.433	-0.645**
	(0.394)	(0.361)	(0.235)	(0.265)	(0.333)	(0.282)
4 quarters before contract	0.189	0.174	-0.485***	-0.212	-0.495	-0.619**
	(0.323)	(0.352)	(0.162)	(0.237)	(0.306)	(0.246)
3 quarters before contract	0.164	0.191	-0.251***	-0.189	-0.394**	-0.452***
	(0.170)	(0.191)	(0.088)	(0.151)	(0.195)	(0.161)
2 quarters before contract	-0.211*	-0.202	-0.396***	-0.220	-0.316*	-0.356**
	(0.114)	(0.158)	(0.098)	(0.139)	(0.183)	(0.144)
Receiving 1st contract	0.168	0.508*	0.300*	-0.129	-0.054	-0.053
	(0.177)	(0.271)	(0.170)	(0.130)	(0.133)	(0.113)
1 quarter after contract	0.057	0.804**	0.492	-0.096	0.066	0.181
	(0.345)	(0.375)	(0.325)	(0.155)	(0.186)	(0.141)
2 quarters after contract	-0.177	0.847*	0.516	-0.132	0.024	0.325*
	(0.390)	(0.420)	(0.321)	(0.198)	(0.207)	(0.175)
3 quarters after contract	-0.093	1.153*	0.693	-0.049	0.251	0.440**
	(0.600)	(0.600)	(0.477)	(0.251)	(0.247)	(0.217)
4 quarters after contract	0.226	1.892***	1.175*	0.104	0.518	0.718***
	(0.708)	(0.664)	(0.605)	(0.292)	(0.332)	(0.269)
5 quarters after contract	0.316	2.248***	1.628**	0.205	0.753*	1.017***
	(0.789)	(0.748)	(0.643)	(0.348)	(0.437)	(0.347)
6 quarters after contract	0.641	3.179***	2.220**	0.420	1.214**	1.385***
	(1.053)	(1.013)	(0.859)	(0.437)	(0.580)	(0.465)
7 quarters after contract	0.866	3.007***	2.753***	0.637	1.346**	1.807***
	(1.196)	(0.995)	(0.844)	(0.538)	(0.637)	(0.569)
8 quarters after contract	1.294	3.196***	3.225***	0.700	1.495**	2.037***
	(0.767)	(1.054)	(0.880)	(0.491)	(0.712)	(0.642)
8 quarters before contract × public security	-0.207	0.108	-0.238	0.322	0.685	0.152
	(0.486)	(0.609)	(0.465)	(0.513)	(0.688)	(0.499)
7 quarters before contract × public security	-0.497	-0.236	-0.394	0.258	0.556	0.133
	(0.423)	(0.513)	(0.343)	(0.327)	(0.442)	(0.307)
6 quarters before contract × public security	-0.098	-0.021	-0.020	0.207	0.532	0.097
	(0.347)	(0.516)	(0.341)	(0.330)	(0.412)	(0.338)
5 quarters before contract × public security	0.239	0.043	0.317	0.299	0.622	0.168
	(0.273)	(0.466)	(0.324)	(0.247)	(0.392)	(0.244)
4 quarters before contract × public security	0.129	-0.042	0.261	0.229	0.478	0.145
	(0.238)	(0.436)	(0.285)	(0.232)	(0.366)	(0.224)
3 quarters before contract × public security	0.019	0.018	0.113	0.185	0.434*	0.116
	(0.171)	(0.228)	(0.249)	(0.143)	(0.231)	(0.140)
2 quarters before contract × public security	-0.182	0.015	-0.193	-0.032	0.175	-0.086
	(0.172)	(0.335)	(0.169)	(0.182)	(0.277)	(0.170)
Receiving 1st contract × public security	0.195	-0.111	0.096	0.435**	0.403**	0.448***
	(0.197)	(0.385)	(0.189)	(0.185)	(0.201)	(0.152)
1 quarter after contract × public security	1.000**	0.045	0.545	0.819***	0.551	0.633***

	(0.446)	(0.617)	(0.330)	(0.247)	(0.335)	(0.219)
2 quarters after contract × public security	1.468***	0.417	0.941***	1.342***	1.219***	1.109***
	(0.446)	(0.670)	(0.293)	(0.245)	(0.339)	(0.217)
3 quarters after contract × public security	1.702**	0.303	1.189**	1.437***	1.122***	1.252***
	(0.715)	(0.719)	(0.519)	(0.330)	(0.369)	(0.274)
4 quarters after contract × public security	1.720*	-0.070	1.243	1.568***	1.144**	1.438***
	(0.935)	(0.958)	(0.738)	(0.478)	(0.528)	(0.408)
5 quarters after contract × public security	1.739	-0.486	1.042	1.849***	1.202*	1.550***
	(1.071)	(0.994)	(0.834)	(0.566)	(0.651)	(0.515)
6 quarters after contract × public security	1.780	-0.739	1.076	1.878***	1.067	1.521**
	(1.245)	(1.244)	(1.090)	(0.622)	(0.727)	(0.600)
7 quarters after contract × public security	2.261	0.056	1.406	2.149***	1.348*	1.732**
	(1.673)	(1.312)	(1.407)	(0.793)	(0.793)	(0.763)
8 quarters after contract × public security	2.123*	-0.174	1.320	2.403***	1.416	1.955**
	(1.249)	(1.465)	(1.063)	(0.767)	(0.917)	(0.755)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in government software production between firms that earn politically motivated (public security) contracts versus non-politically motivated contracts. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.11: Differential effect of politically-motivated public security contracts on commercial software production

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
8 quarters before contract	2.120	1.463	0.158	0.618	0.157	-0.337
	(1.397)	(0.866)	(0.387)	(0.684)	(0.452)	(0.227)
7 quarters before contract	1.754	1.153	0.117	0.527	0.181	-0.284
	(1.196)	(0.777)	(0.338)	(0.567)	(0.405)	(0.187)
6 quarters before contract	1.321	1.066	0.019	0.488	0.346	-0.160
	(0.917)	(0.713)	(0.268)	(0.476)	(0.380)	(0.160)
5 quarters before contract	0.608	0.251	-0.430**	0.220	-0.052	-0.300**
	(0.481)	(0.309)	(0.171)	(0.265)	(0.207)	(0.133)
4 quarters before contract	0.350	0.125	-0.417***	-0.007	-0.205	-0.426***
	(0.381)	(0.265)	(0.113)	(0.222)	(0.145)	(0.115)
3 quarters before contract	0.192	0.020	-0.284***	-0.111	-0.274*	-0.352***
	(0.217)	(0.123)	(0.082)	(0.160)	(0.141)	(0.111)
2 quarters before contract	-0.103	-0.101	-0.271***	0.006	-0.014	-0.103
	(0.077)	(0.112)	(0.096)	(0.099)	(0.117)	(0.077)
Receiving 1st contract	-0.106	0.055	0.007	-0.275	0.184*	-0.194
	(0.135)	(0.121)	(0.064)	(0.461)	(0.103)	(0.399)
1 quarter after contract	-0.973	0.214	-0.532	-0.364	0.206	-0.112
	(0.909)	(0.178)	(0.710)	(0.517)	(0.143)	(0.384)
2 quarters after contract	-1.179	0.369	-0.303	-0.287	0.412**	0.190
	(1.088)	(0.280)	(0.724)	(0.630)	(0.199)	(0.418)
3 quarters after contract	-1.444	0.133	-0.510	-0.289	0.472**	0.192
	(1.302)	(0.299)	(0.820)	(0.718)	(0.217)	(0.455)
4 quarters after contract	-1.362	0.581	-0.299	-0.215	0.691**	0.402
	(1.445)	(0.428)	(0.844)	(0.818)	(0.288)	(0.496)
5 quarters after contract	-1.497	0.557	0.004	-0.192	0.797**	0.629
	(1.456)	(0.452)	(0.656)	(0.859)	(0.345)	(0.455)
6 quarters after contract	-1.451	1.213**	0.402	0.060	1.254***	1.004**
	(1.748)	(0.583)	(0.748)	(0.927)	(0.403)	(0.469)
7 quarters after contract	-2.130	0.688	0.116	-0.151	1.160***	0.982*
	(2.019)	(0.587)	(0.826)	(1.051)	(0.391)	(0.516)
8 quarters after contract	-0.432	0.755	1.857***	0.500	1.210***	1.823***
	(0.828)	(0.638)	(0.658)	(0.539)	(0.418)	(0.459)
8 quarters before contract × public security	-0.556	-0.731	-0.681	-0.115	-0.052	-0.216
	(0.378)	(0.480)	(0.458)	(0.319)	(0.349)	(0.363)
7 quarters before contract × public security	-0.762	-0.690	-0.748	-0.138	-0.016	-0.155
	(0.457)	(0.436)	(0.461)	(0.304)	(0.281)	(0.323)
6 quarters before contract × public security	-0.585*	-0.680	-0.599*	-0.208	-0.225	-0.251
	(0.340)	(0.442)	(0.355)	(0.305)	(0.324)	(0.320)
5 quarters before contract × public security	-0.055	-0.037	-0.129	-0.004	0.124	-0.104
	(0.245)	(0.408)	(0.220)	(0.201)	(0.342)	(0.183)
4 quarters before contract × public security	0.126	-0.007	0.130	0.172	0.218	0.110
	(0.265)	(0.383)	(0.273)	(0.168)	(0.254)	(0.162)
3 quarters before contract × public security	-0.183	-0.243	-0.133	0.152	0.263	0.091
	(0.152)	(0.316)	(0.185)	(0.159)	(0.243)	(0.161)
2 quarters before contract × public security	-0.229	-0.216	-0.308	-0.191	-0.184	-0.263**
	(0.260)	(0.424)	(0.215)	(0.132)	(0.218)	(0.132)
Receiving 1st contract × public security	0.645*	0.226	0.484**	0.685	0.179	0.696
	(0.336)	(0.209)	(0.205)	(0.530)	(0.142)	(0.493)
1 quarter after contract × public security	2.107	0.535	1.585*	1.290**	0.576**	1.121**

	(1.278)	(0.326)	(0.925)	(0.622)	(0.230)	(0.525)
2 quarters after contract × public security	2.349*	0.604	1.759*	1.330**	0.534*	1.097*
	(1.232)	(0.534)	(0.933)	(0.645)	(0.284)	(0.562)
3 quarters after contract × public security	3.004*	0.874	2.350**	1.474**	0.550*	1.347**
	(1.556)	(0.548)	(1.098)	(0.736)	(0.324)	(0.618)
4 quarters after contract × public security	3.523*	0.481	2.828*	1.765*	0.507	1.667*
	(1.997)	(0.864)	(1.457)	(0.971)	(0.444)	(0.842)
5 quarters after contract × public security	3.690*	0.292	2.898**	2.085**	0.552	1.834**
	(1.880)	(1.050)	(1.328)	(1.006)	(0.545)	(0.822)
6 quarters after contract × public security	4.033**	0.469	3.283**	2.254**	0.658	1.964**
	(1.969)	(1.203)	(1.499)	(1.038)	(0.619)	(0.876)
7 quarters after contract × public security	5.701**	1.522	4.735**	3.132**	1.220*	2.777**
	(2.595)	(1.399)	(2.053)	(1.313)	(0.644)	(1.137)
8 quarters after contract × public security	5.516**	2.001	4.510***	3.193***	1.511**	2.779***
	(2.186)	(1.634)	(1.529)	(1.028)	(0.655)	(0.801)
Regression	OLS	OLS	OLS	IV	IV	IV
Firm characteristics	No	Yes	No	No	Yes	No
Event-study weighting	No	No	Yes	No	No	Yes

Notes: The table presents regression coefficients for facial recognition AI firms that earn contracts from local governments when there is an above median amount of unrest in the quarter prior to the contract. The table shows the difference in commercial software production between firms that earn politically motivated (public security) contracts versus non-politically motivated contracts. In the IV specification (columns 4-6), local unrest is instrumented by weather variables selected by LASSO. All columns control for time period fixed effects and firm fixed effects. Columns 2 and 5 include control for the time-varying effects of the contract and company size (an inverse covariance weighted z-score for contract size and company size interacted with year indicators, following Anderson (2008)). Columns 3 and 6 weight the control group by 1000 times more than the treatment, following Borusyak et al. (2017). Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.12: Total effect of politically-motivated AI procurement on innovation: robustness and evaluating alternative hypotheses

	All		Government		Commercial	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.1: Baseline result						
8 quarters before contract	3.209	1.784	1.479	0.676	1.564	0.503
	(3.440)	(1.730)	(1.163)	(0.757)	(1.448)	(0.755)
8 quarters after contract	10.723***	9.376***	3.417**	3.103***	5.085**	3.693***
	(3.585)	(2.131)	(1.466)	(0.911)	(2.338)	(1.161)
Panel A.2: Control for firm age × year to/from contract receipt indicators						
8 quarters before contract	2.908	1.327	1.233	0.479	1.520	0.408
	(3.463)	(1.673)	(1.252)	(0.696)	(1.507)	(0.772)
8 quarters after contract	10.692***	9.154***	3.322**	2.972***	5.152**	3.656***
	(3.320)	(2.021)	(1.478)	(0.887)	(2.356)	(1.137)
Panel A.3: Control for pre-contract software production × year to/from contract receipt indicators						
8 quarters before contract	3.159	1.812	1.456	0.653	1.592	0.529
	(3.543)	(1.681)	(1.172)	(0.731)	(1.468)	(0.760)
8 quarters after contract	10.472***	8.932***	3.136**	3.017***	5.024**	3.578***
	(3.580)	(2.196)	(1.434)	(0.937)	(2.366)	(1.163)
Panel A.4: Control for pre-contract firm capitalization × year to/from contract receipt indicators						
8 quarters before contract	3.209	1.784	1.479	0.676	1.564	0.503
	(3.440)	(1.730)	(1.163)	(0.757)	(1.448)	(0.755)
8 quarters after contract	10.723***	9.376***	3.417**	3.103***	5.085**	3.693***
	(3.585)	(2.131)	(1.466)	(0.911)	(2.338)	(1.161)
Panel A.5: Control for contract size × year to/from contract receipt indicators						
8 quarters before contract	1.706	1.120	1.023	0.663	0.677	0.138
	(2.569)	(1.730)	(0.831)	(0.979)	(0.932)	(0.558)
8 quarters after contract	8.609*	8.185***	2.973	2.906**	2.777	2.735***
	(4.366)	(2.053)	(1.775)	(1.129)	(1.761)	(0.777)
Panel A.6: Control for pre-contract firm productivity index × year to/from contract receipt indicators						
8 quarters before contract	3.286	1.697	1.520	0.655	1.572	0.543
	(3.432)	(1.747)	(1.145)	(0.772)	(1.458)	(0.852)
8 quarters after contract	10.719***	9.239***	3.436**	3.115***	5.082**	3.715***
	(3.844)	(2.089)	(1.509)	(0.914)	(2.348)	(1.146)
Panel B: Only major software releases						
8 quarters before contract	3.354	1.763	1.526	0.650	1.558	0.536
	(3.550)	(1.757)	(1.236)	(0.698)	(1.448)	(0.760)
8 quarters after contract	10.774***	9.287***	3.456**	3.086***	5.023**	3.688***
	(3.824)	(2.142)	(1.562)	(0.913)	(2.408)	(1.167)
Panel C: Drop ambiguous public security agencies						
8 quarters before contract	3.644	2.106	1.576	0.800	1.736	0.649
	(4.167)	(2.191)	(1.411)	(0.836)	(1.781)	(0.937)
8 quarters after contract	10.360***	9.180***	3.209**	3.041***	5.037*	3.658***

	(3.516)	(2.184)	(1.256)	(0.919)	(2.689)	(1.235)
Panel D.1: LSTM categorization model configuration (vary timestep = 10)						
8 quarters before contract	3.338	1.711	0.648	0.183	1.563	0.889
	(3.161)	(1.713)	(0.812)	(0.626)	(1.784)	(1.027)
8 quarters after contract	10.797***	9.288***	2.871*	2.875***	6.116	4.523*
	(3.941)	(2.153)	(1.477)	(0.883)	(4.637)	(2.342)
Panel D.2: LSTM categorization model configuration (vary embeddings = 16)						
8 quarters before contract	3.279	1.813	1.451	0.338	1.335	0.951
	(3.570)	(1.775)	(1.725)	(0.889)	(1.374)	(0.967)
8 quarters after contract	10.681***	9.309***	3.930***	3.712***	5.362	3.933**
	(3.828)	(2.115)	(1.325)	(0.955)	(3.959)	(1.927)
Panel D.3: LSTM categorization model configuration (vary nodes = 16)						
8 quarters before contract	3.295	1.795	0.578	0.099	1.920	1.055
	(3.588)	(1.987)	(0.966)	(0.684)	(1.779)	(1.016)
8 quarters after contract	10.672***	9.268***	3.563**	3.558***	5.082	3.523
	(3.839)	(2.114)	(1.512)	(0.893)	(4.953)	(2.338)
Panel E.1: Time frame (full balanced panel)						
8 quarters before contract	3.233	1.645	1.468	0.758	1.519	0.519
	(3.451)	(1.700)	(1.171)	(0.727)	(1.586)	(0.718)
8 quarters after contract	10.726***	9.317***	3.428**	3.147***	5.040**	3.757***
	(3.616)	(2.186)	(1.495)	(0.906)	(2.275)	(1.135)
Panel E.2: Time frame (extended time frame)						
8 quarters before contract	3.675	1.890	1.812	0.899	2.464	1.076
	(4.259)	(2.072)	(1.449)	(0.812)	(1.832)	(0.939)
18 quarters after contract	23.580**	19.890***	10.691***	6.789***	8.048**	5.669***
	(11.224)	(6.779)	(3.407)	(1.490)	(3.293)	(1.125)
Panel F.1: Access to commercial opportunities - control Beijing/Shanghai × year to/from contract receipt indicators						
8 quarters before contract	2.321	1.593	1.197	0.678	1.210	0.494
	(2.856)	(1.633)	(1.003)	(0.729)	(1.185)	(0.749)
8 quarters after contract	12.706***	10.427***	4.004**	3.396***	6.010**	4.281***
	(4.271)	(2.622)	(1.687)	(0.994)	(2.789)	(1.445)
Panel F.2: Access to commercial opportunities - contracts outside of Xinjiang						
8 quarters before contract	2.907	1.674	1.311	0.804	1.670	0.779
	(3.562)	(1.878)	(1.219)	(0.822)	(1.554)	(1.179)
8 quarters after contract	10.421***	9.266***	3.249**	3.232***	5.191**	3.968***
	(3.575)	(2.157)	(1.430)	(0.913)	(2.308)	(1.066)
Panel F.3: Access to commercial opportunities - firm based outside contract prefecture						
8 quarters before contract	3.208	1.704	1.473	0.677	1.547	0.542
	(3.649)	(1.741)	(1.175)	(0.692)	(1.670)	(0.741)
8 quarters after contract	10.639***	9.328***	3.420**	3.106***	5.106**	3.724***
	(3.677)	(2.127)	(1.479)	(0.906)	(2.258)	(1.140)
Panel F.4: Access to commercial opportunities - firm based outside contract province						
8 quarters before contract	3.208	1.704	1.526	0.733	1.545	0.495
	(3.649)	(1.741)	(1.179)	(0.788)	(1.566)	(0.737)

8 quarters after contract	10.639***	9.328***	3.426**	3.102***	5.051**	3.706***
	(3.677)	(2.127)	(1.511)	(0.916)	(2.219)	(1.157)
Panel G: Control for province by quarter fixed effects						
8 quarters before contract	2.594	1.396	1.159	0.551	1.345	0.456
	(3.128)	(1.680)	(1.082)	(0.621)	(1.310)	(0.797)
8 quarters after contract	13.010***	10.484***	4.027**	3.332***	6.170**	4.495***
	(4.638)	(2.648)	(1.815)	(1.015)	(2.861)	(1.453)
Panel H: Video AI software production						
8 quarters before contract	0.285	0.183				
	(0.344)	(0.237)				
8 quarters after contract	1.169	1.045***				
	(0.767)	(0.382)				

Notes: Specifications include full set of time indicators with politically motivated (public security) contracts; only selected coefficient estimates are presented. Panel A.1 replicates the baseline specification in Table 5, Panel A.2 adds controls for firm age interacted with time indicators of years to/from contract receipt, Panel A.3 adds controls for pre-contract firm software production interacted with time indicators of years to/from contract receipt, Panel A.4 adds controls for pre-contract firm capitalization interacted with time indicators of years to/from contract receipt, Panel A.5 adds controls for contract monetary size interacted with time indicators of years to/from contract receipt, and Panel A.6 adds controls for an index of firms' underlying productivity (an inverse covariance weighted z-score of firms' establishment year, pre-contract capitalization, rounds of external financing prior to their first procurement contract, and total pre-contract software production) interacted with time indicators of years to/from contract receipt. Panel B uses only major software releases (version X.0). Panel C drops companies whose first contract is an ambiguous contract, or one that contains the keywords 'local government' ('人民政府') or 'government offices' ('政府办公室') which may be used for either public security or non-public security depending on interpretation. The baseline LSTM specification uses a timestep (phrase length) of 20, embedding size (number of dimensions in a vector to represent a phrase) of 32, and 32 nodes in the model. Panel D.1 presents results for the baseline model trained with a timestep of 10, Panel D.2 presents results for for the baseline model trained with an embedding size of 16, and Panel D.3 presents results for the baseline model trained with 16 nodes. Panel E.1 restricts the sample to firms that have non-missing observations during the entire time frame of 8 quarters before and 8 quarters after the initial contracts; Panel E.2 extends the time frame to 9 quarters before and 18 quarters after the initial contracts. Panel F.1 includes fixed effects for contracts from Beijing and Shanghai (the two highest capacity prefectures/provinces) interacted with time indicators of years to/from contract receipt, Panel F.2 omits contracts from Xinjiang, Panel F.3 restricts the analysis to firms that have their first contract outside of their home prefecture, and Panel F.4 restricts to firms with first contract outside their home province. Panel G adds fixed effects at the province by quarter level. Panel H uses video AI software production as the outcome with columns 1 and 2 continuing to show OLS and IV. Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.13: Differential effect of politically-motivated AI procurement on innovation: robustness and evaluating alternative hypotheses

	All		Government		Commercial	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.1: Baseline result						
8 quarters before contract	4.898	1.210	1.686	0.354	2.120	0.618
	(3.216)	(1.305)	(1.056)	(0.557)	(1.397)	(0.684)
8 quarters after contract	0.977	1.864*	1.294	0.700	-0.432	0.500
	(1.521)	(1.024)	(0.767)	(0.491)	(0.828)	(0.539)
8 quarters before contract × public security	-1.690	0.574	-0.207	0.322	-0.556	-0.115
	(1.220)	(1.136)	(0.486)	(0.513)	(0.378)	(0.319)
8 quarters after contract × public security	9.746***	7.512***	2.123*	2.403***	5.516**	3.193***
	(3.246)	(1.869)	(1.249)	(0.767)	(2.186)	(1.028)
Panel A.2: Control for firm age × year to/from contract receipt indicators						
8 quarters before contract	4.816	1.135	1.719	0.155	2.142	0.614
	(3.300)	(1.310)	(1.155)	(0.453)	(1.459)	(0.699)
8 quarters after contract	1.263	2.075**	1.314*	0.776	-0.328	0.579
	(1.298)	(0.989)	(0.727)	(0.496)	(0.753)	(0.518)
8 quarters before contract × public security	-1.907*	0.192	-0.486	0.324	-0.621	-0.206
	(1.049)	(1.042)	(0.484)	(0.528)	(0.378)	(0.328)
8 quarters after contract × public security	9.429***	7.078***	2.008	2.196***	5.480**	3.077***
	(3.056)	(1.762)	(1.287)	(0.735)	(2.232)	(1.012)
Panel A.3: Control for pre-contract software production × year to/from contract receipt indicators						
8 quarters before contract	4.741	1.150	1.546	0.404	2.149	0.579
	(3.322)	(1.296)	(1.077)	(0.532)	(1.416)	(0.686)
8 quarters after contract	1.061	1.874*	1.347*	0.831	-0.381	0.408
	(1.506)	(1.045)	(0.739)	(0.510)	(0.828)	(0.528)
8 quarters before contract × public security	-1.582	0.662	-0.091	0.249	-0.556	-0.050
	(1.232)	(1.069)	(0.461)	(0.502)	(0.388)	(0.327)
8 quarters after contract × public security	9.411***	7.059***	1.789	2.186***	5.405**	3.170***
	(3.248)	(1.931)	(1.229)	(0.786)	(2.217)	(1.036)
Panel A.4: Control for pre-contract firm capitalization × year to/from contract receipt indicators						
8 quarters before contract	4.898	1.210	1.686	0.354	2.120	0.618
	(3.216)	(1.305)	(1.056)	(0.557)	(1.397)	(0.684)
8 quarters after contract	0.977	1.864*	1.294	0.700	-0.432	0.500
	(1.521)	(1.024)	(0.767)	(0.491)	(0.828)	(0.539)
8 quarters before contract × public security	-1.690	0.574	-0.207	0.322	-0.556	-0.115
	(1.220)	(1.136)	(0.486)	(0.513)	(0.378)	(0.319)
8 quarters after contract × public security	9.746***	7.512***	2.123*	2.403***	5.516**	3.193***
	(3.246)	(1.869)	(1.249)	(0.767)	(2.186)	(1.028)
Panel A.5: Control for contract size × year to/from contract receipt indicators						
8 quarters before contract	3.289	0.058	0.823	-0.066	1.370	0.173
	(2.177)	(1.135)	(0.632)	(0.704)	(0.817)	(0.445)
8 quarters after contract	4.390**	3.645***	3.030***	1.361*	0.727	1.079**
	(1.941)	(1.258)	(1.030)	(0.685)	(0.663)	(0.419)
8 quarters before contract × public security	-1.584	1.062	0.200	0.729	-0.694	-0.035

	(1.364)	(1.306)	(0.540)	(0.681)	(0.449)	(0.336)
8 quarters after contract × public security	4.219	4.540***	-0.056	1.545*	2.050	1.656**
	(3.911)	(1.623)	(1.445)	(0.897)	(1.631)	(0.654)
Panel A.6: Control for pre-contract firm productivity index × year to/from contract receipt indicators						
8 quarters before contract	5.029	1.337	1.654	0.346	2.132	0.684
	(3.247)	(1.365)	(1.034)	(0.563)	(1.405)	(0.756)
8 quarters after contract	0.896	1.809*	1.237	0.711	-0.453	0.504
	(1.671)	(1.016)	(0.785)	(0.490)	(0.838)	(0.524)
8 quarters before contract × public security	-1.743	0.360	-0.135	0.309	-0.559	-0.140
	(1.111)	(1.091)	(0.492)	(0.528)	(0.387)	(0.392)
8 quarters after contract × public security	9.823***	7.430***	2.199*	2.404***	5.536**	3.211***
	(3.461)	(1.825)	(1.288)	(0.771)	(2.194)	(1.019)
Panel B: Only major software releases						
8 quarters before contract	5.166	1.277	1.808	0.234	2.084	0.603
	(3.345)	(1.326)	(1.133)	(0.488)	(1.404)	(0.686)
8 quarters after contract	0.814	1.803*	1.252	0.702	-0.455	0.511
	(1.670)	(1.042)	(0.805)	(0.489)	(0.884)	(0.543)
8 quarters before contract × public security	-1.811	0.486	-0.282	0.415	-0.525	-0.066
	(1.189)	(1.153)	(0.494)	(0.499)	(0.353)	(0.328)
8 quarters after contract × public security	9.960***	7.484***	2.204	2.384***	5.478**	3.177***
	(3.440)	(1.871)	(1.339)	(0.771)	(2.240)	(1.033)
Panel C: Drop ambiguous public security agencies						
8 quarters before contract	5.268	1.682	1.825	0.232	2.297	0.780
	(3.860)	(1.709)	(1.264)	(0.558)	(1.698)	(0.837)
8 quarters after contract	1.653	2.242**	1.847**	1.049*	-0.369	0.572
	(1.365)	(1.061)	(0.734)	(0.537)	(0.847)	(0.491)
8 quarters before contract × public security	-1.624	0.424	-0.248	0.568	-0.561	-0.132
	(1.572)	(1.370)	(0.627)	(0.622)	(0.537)	(0.422)
8 quarters after contract × public security	8.707**	6.938***	1.362	1.992***	5.405**	3.086***
	(3.240)	(1.908)	(1.019)	(0.746)	(2.552)	(1.133)
Panel D.1: LSTM categorization model configuration (vary timestep = 10)						
8 quarters before contract	4.787	1.308	1.027	-0.083	2.061	0.753
	(3.013)	(1.337)	(0.661)	(0.421)	(1.670)	(0.776)
8 quarters after contract	0.746	1.780*	1.351	1.183**	-1.461	-0.226
	(1.756)	(1.055)	(0.910)	(0.522)	(1.600)	(0.975)
8 quarters before contract × public security	-1.449	0.403	-0.380	0.266	-0.499	0.136
	(0.956)	(1.071)	(0.471)	(0.463)	(0.629)	(0.672)
8 quarters after contract × public security	10.052***	7.508***	1.520	1.692**	7.577*	4.749**
	(3.529)	(1.876)	(1.164)	(0.712)	(4.353)	(2.130)
Panel D.2: LSTM categorization model configuration (vary embeddings = 16)						
8 quarters before contract	5.153	1.287	2.510	0.600	1.532	0.371
	(3.355)	(1.350)	(1.614)	(0.722)	(1.309)	(0.721)
8 quarters after contract	0.809	1.796*	1.775*	1.621***	-1.125	-0.206
	(1.705)	(1.023)	(0.919)	(0.595)	(1.492)	(0.850)
8 quarters before contract × public security	-1.874	0.526	-1.059*	-0.262	-0.197	0.579
	(1.219)	(1.153)	(0.609)	(0.519)	(0.416)	(0.644)
8 quarters after contract × public security	9.872***	7.512***	2.155**	2.091***	6.487*	4.140**
	(3.427)	(1.851)	(0.954)	(0.747)	(3.667)	(1.730)

Panel D.3: LSTM categorization model configuration (vary nodes = 16)						
8 quarters before contract	5.182	1.535	1.215	-0.105	2.258	0.735
	(3.372)	(1.544)	(0.774)	(0.432)	(1.680)	(0.792)
8 quarters after contract	0.777	1.812*	1.736**	1.672***	-1.646	-0.794
	(1.703)	(1.027)	(0.854)	(0.504)	(1.563)	(0.918)
8 quarters before contract × public security	-1.887	0.260	-0.637	0.205	-0.338	0.320
	(1.228)	(1.251)	(0.578)	(0.531)	(0.584)	(0.637)
8 quarters after contract × public security	9.895***	7.456***	1.827	1.886**	6.727	4.317**
	(3.441)	(1.848)	(1.248)	(0.737)	(4.700)	(2.150)
Panel E.1: Time frame (full balanced panel)						
8 quarters before contract	4.887	1.258	1.686	0.243	2.204	0.587
	(3.229)	(1.318)	(1.059)	(0.494)	(1.504)	(0.654)
8 quarters after contract	0.940	1.782*	1.247	0.711	-0.426	0.542
	(1.539)	(1.070)	(0.776)	(0.483)	(0.800)	(0.493)
8 quarters before contract × public security	-1.654	0.387	-0.218	0.514	-0.685	-0.068
	(1.219)	(1.073)	(0.499)	(0.533)	(0.503)	(0.297)
8 quarters after contract × public security	9.786***	7.535***	2.180*	2.436***	5.466**	3.215***
	(3.272)	(1.906)	(1.278)	(0.766)	(2.129)	(1.023)
Panel E.2: Time frame (extended time frame)						
9 quarters before contract	4.839	1.197	1.653	0.250	2.143	0.572
	(3.988)	(1.684)	(1.372)	(0.613)	(1.812)	(0.900)
18 quarters after contract	11.333	-0.479	3.163	-1.705**	3.092	0.110
	(9.340)	(2.419)	(2.857)	(0.654)	(2.567)	(0.498)
9 quarters before contract × public security	-1.164	0.693	0.159	0.649	0.321	0.504*
	(1.493)	(1.207)	(0.466)	(0.532)	(0.269)	(0.267)
18 quarters after contract × public security	12.247*	20.370***	7.528***	8.494***	4.956**	5.559***
	(6.225)	(6.333)	(1.856)	(1.338)	(2.062)	(1.008)
Panel F.1: Access to commercial opportunities - control Beijing/Shanghai × year to/from contract receipt indicators						
8 quarters before contract	3.834	1.058	1.356	0.340	1.613	0.586
	(2.731)	(1.295)	(0.919)	(0.544)	(1.169)	(0.705)
8 quarters after contract	1.636	2.233**	1.487**	0.827*	-0.170	0.694*
	(1.121)	(0.855)	(0.700)	(0.476)	(0.614)	(0.403)
8 quarters before contract × public security	-1.512*	0.535	-0.159	0.338	-0.403**	-0.092
	(0.835)	(0.995)	(0.403)	(0.486)	(0.195)	(0.255)
8 quarters after contract × public security	11.071**	8.194***	2.517	2.569***	6.181**	3.587**
	(4.121)	(2.479)	(1.535)	(0.873)	(2.721)	(1.387)
Panel F.2: Access to commercial opportunities - contracts outside of Xinjiang						
8 quarters before contract	4.597	1.100	1.519	0.483	2.226	0.893
	(3.347)	(1.496)	(1.118)	(0.642)	(1.507)	(1.136)
8 quarters after contract	0.676	1.753	1.126	0.829*	-0.325	0.775***
	(1.498)	(1.076)	(0.695)	(0.496)	(0.742)	(0.282)
8 quarters before contract × public security	-1.690	0.574	-0.207	0.322	-0.556	-0.115
	(1.220)	(1.136)	(0.486)	(0.513)	(0.378)	(0.319)
8 quarters after contract × public security	9.746***	7.512***	2.123*	2.403***	5.516**	3.193***
	(3.246)	(1.869)	(1.249)	(0.767)	(2.186)	(1.028)
Panel F.3: Access to commercial opportunities - firm based outside contract prefecture						
8 quarters before contract	5.184	1.238	1.688	0.255	2.301	0.573

	(3.400)	(1.316)	(1.068)	(0.484)	(1.576)	(0.666)
8 quarters after contract	0.921	1.876*	1.291	0.717	-0.390	0.541
	(1.628)	(1.040)	(0.777)	(0.490)	(0.795)	(0.513)
8 quarters before contract × public security	-1.977	0.467	-0.216	0.422	-0.754	-0.031
	(1.324)	(1.140)	(0.490)	(0.494)	(0.553)	(0.324)
8 quarters after contract × public security	9.718***	7.452***	2.129*	2.389***	5.497**	3.183***
	(3.297)	(1.856)	(1.258)	(0.762)	(2.114)	(1.018)
Panel F.4: Access to commercial opportunities - firm based outside contract province						
8 quarters before contract	5.184	1.238	1.718	0.347	2.193	0.600
	(3.400)	(1.316)	(1.079)	(0.556)	(1.496)	(0.668)
8 quarters after contract	0.921	1.876*	1.254	0.702	-0.356	0.508
	(1.628)	(1.040)	(0.789)	(0.493)	(0.762)	(0.532)
8 quarters before contract × public security	-1.977	0.467	-0.191	0.387	-0.648	-0.105
	(1.324)	(1.140)	(0.476)	(0.559)	(0.461)	(0.311)
8 quarters after contract × public security	9.718***	7.452***	2.172	2.400***	5.408**	3.198***
	(3.297)	(1.856)	(1.288)	(0.772)	(2.084)	(1.027)
Panel G: Control for province by quarter fixed effects						
8 quarters before contract	4.161	1.156	1.393	0.188	1.744	0.589
	(3.020)	(1.412)	(0.997)	(0.463)	(1.298)	(0.752)
8 quarters after contract	2.313**	2.525***	1.869**	0.802	0.308	0.984***
	(1.014)	(0.901)	(0.694)	(0.498)	(0.383)	(0.369)
8 quarters before contract × public security	-1.567*	0.239	-0.234	0.363	-0.398**	-0.133
	(0.816)	(0.911)	(0.419)	(0.414)	(0.172)	(0.264)
8 quarters after contract × public security	10.697**	7.959***	2.158	2.530***	5.862**	3.510**
	(4.526)	(2.490)	(1.677)	(0.885)	(2.835)	(1.405)
Panel H: Video AI software production						
8 quarters before contract	0.482	0.119				
	(0.308)	(0.174)				
8 quarters after contract	0.002	0.142				
	(0.335)	(0.194)				
8 quarters before contract × public security	-0.197	0.064				
	(0.154)	(0.160)				
8 quarters after contract × public security	1.167*	0.904***				
	(0.690)	(0.329)				

Notes: Specifications include full set of time indicators and interactions with politically motivated (public security) contracts; only selected coefficient estimates are presented. Panel A.1 replicates the baseline specification in Table A.9, Panel A.2 adds controls for firm age interacted with time indicators of years to/from contract receipt, Panel A.3 adds controls for pre-contract firm software production interacted with time indicators of years to/from contract receipt, Panel A.4 adds controls for pre-contract firm capitalization interacted with time indicators of years to/from contract receipt, Panel A.5 adds controls for contract monetary size interacted with time indicators of years to/from contract receipt, and Panel A.6 adds controls for an index of firms' underlying productivity (an inverse covariance weighted z-score of firms' establishment year, pre-contract capitalization, rounds of external financing prior to their first procurement contract, and total pre-contract software production) interacted with time indicators of years to/from contract receipt. Panel B uses only major software releases (version X.0). Panel C drops companies whose first contract is an ambiguous contract, or one that contains the keywords 'local government' ('人民政府') or 'government offices' ('政府办公室') which may be used for either public security or non-public security depending on interpretation.

The baseline LSTM specification uses a timestep (phrase length) of 20, embedding size (number of dimensions in a vector to represent a phrase) of 32, and 32 nodes in the model. Panel D.1 presents results for the baseline model trained with a timestep of 10, Panel D.2 presents results for for the baseline model trained with an embedding size of 16, and Panel D.3 presents results for the baseline model trained with 16 nodes. Panel E.1 restricts the sample to firms that have non-missing observations during the entire time frame of 8 quarters before and 8 quarters after the initial contracts; Panel E.2 extends the time frame to 9 quarters before and 18 quarters after the initial contracts. Panel F.1 includes fixed effects for contracts from Beijing and Shanghai (the two highest capacity prefectures/provinces) interacted with time indicators of years to/from contract receipt, Panel F.2 omits contracts from Xinjiang, Panel F.3 restricts the analysis to firms that have their first contract outside of their home prefecture, and Panel F.4 restricts to firms with first contract outside their home province. Panel G adds fixed effects at the province by quarter level. Panel H uses video AI software production as the outcome with columns 1 and 2 continuing to show OLS and IV. Standard errors are clustered at the contract location (prefecture) level. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.14: Effect of AI procurement on suppressing unrest — by type of unrest

	Standardized number of unrest events			
	(1)	(2)	(3)	(4)
Panel A.1: Protests, public security				
Favorable weather	0.5150***	0.4759***	0.5143***	0.4759***
	(0.0837)	(0.0649)	(0.0840)	(0.0630)
Public security procurement stock AI_{t-1}	-0.0065	-0.0059	-0.0052	-0.0034
	(0.0055)	(0.0066)	(0.0044)	(0.0065)
Favorable weather × public security AI_{t-1}	-0.1761*	-0.1476**	-0.1763**	-0.1494**
	(0.0901)	(0.0668)	(0.0885)	(0.0646)
Panel A.2: Demands, public security				
Favorable weather	1.0632***	1.1096***	1.0634***	1.1071***
	(0.1784)	(0.1726)	(0.1789)	(0.1661)
Public security procurement stock AI_{t-1}	0.0030	0.0019	0.0031	0.0015
	(0.0146)	(0.0127)	(0.0146)	(0.0120)
Favorable weather × public security AI_{t-1}	-0.0553	-0.1079	-0.0556	-0.1020
	(0.1565)	(0.1345)	(0.1543)	(0.1289)
Panel A.3: Threats, public security				
Favorable weather	0.9785***	1.0407***	0.9802***	1.0396***
	(0.2574)	(0.2496)	(0.2581)	(0.2415)
Public security procurement stock AI_{t-1}	-0.0140	-0.0045	-0.0146	-0.0030
	(0.0091)	(0.0101)	(0.0089)	(0.0099)
Favorable weather × public security AI_{t-1}	-0.3274	-0.4040*	-0.3261	-0.3932*
	(0.2161)	(0.2396)	(0.2171)	(0.2331)
Panel B.1: Protests, non-public security				
Favorable weather	0.5303***	0.4885***	0.5295***	0.4888***
	(0.0876)	(0.0670)	(0.0879)	(0.0652)
Non-public security procurement stock AI_{t-1}	-0.0011*	-0.0007	-0.0011*	-0.0005
	(0.0006)	(0.0007)	(0.0006)	(0.0005)
Favorable weather × non-public security AI_{t-1}	-0.0039	0.0011	-0.0036	-0.0011
	(0.0175)	(0.0209)	(0.0180)	(0.0183)
Panel B.2: Demands, non-public security				
Favorable weather	1.0687***	1.1201***	1.0690***	1.1167***
	(0.1856)	(0.1795)	(0.1861)	(0.1725)
Non-public security procurement stock AI_{t-1}	-0.0027*	-0.0036*	-0.0027*	-0.0034*
	(0.0015)	(0.0020)	(0.0015)	(0.0019)
Favorable weather × non-public security AI_{t-1}	-0.0453	-0.0528	-0.0459	-0.0472
	(0.0359)	(0.0403)	(0.0368)	(0.0346)
Panel B.3: Threats, non-public security				
Favorable weather	1.0076***	1.0769***	1.0092***	1.0744***
	(0.2685)	(0.2602)	(0.2692)	(0.2517)
Non-public security procurement stock AI_{t-1}	-0.0021	-0.0020	-0.0021	-0.0017
	(0.0015)	(0.0018)	(0.0015)	(0.0016)
Favorable weather × non-public security AI_{t-1}	-0.0603	-0.0727	-0.0607	-0.0670
	(0.0477)	(0.0545)	(0.0486)	(0.0490)
GDP × quarter	Yes	No	No	Yes
Log population × quarter	No	Yes	No	Yes
Gov. revenue × quarter	No	No	Yes	Yes

Notes: This table follows Table 4 Panels A and B, and presents regressions at the prefecture-quarter level. The dependent variable of interest in Panels X.1 restrict unrest to only protests, Panels X.2 restrict unrest events to only demands, and Panels X.3 restrict unrest events to only threats, all of which are standardized. Favorable weather is the standardized number of predicted events from the good weather LASSO variables interacted with whether there was an event elsewhere in China on the day. AI (public security AI contracts per capita in Panel A, non-public security in Panel B) is also standardized. Prefecture and quarter fixed effects are included. Column 1 controls for prefecture GDP × quarter fixed effects, column 2 controls for log prefecture population × quarter fixed effects, column 3 controls for prefectural government tax revenue × quarter fixed effects, and column 4 adds all prior controls. Standard errors are clustered by prefecture. * significant at 10% ** significant at 5% *** significant at 1%.