The Political Economy Consequences of China's Export Slowdown*

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Abstract

We study how adverse economic shocks influence political outcomes in strong authoritarian regimes, by examining the export slowdown in China between 2013-2015. We exploit detailed customs data and the variation they reveal about Chinese prefectures' underlying exposure to the global trade slowdown, in order to implement a shift-share instrumental variables strategy. Prefectures that experienced a more severe export slowdown witnessed a significant increase in incidents of labor strikes. This was accompanied by a heightened emphasis in such prefectures on upholding domestic stability, as evidenced from: (i) textual analysis measures constructed from official prefecture annual work reports; and (ii) data gathered on local fiscal expenditures channelled towards public security uses and social spending. The central government was subsequently more likely to replace the party secretary in prefectures that saw a high level of "excess strikes", above what could be predicted from the observed export slowdown, suggesting that local leaders were held to account on yardsticks related to political stability.

Keywords: Economic shocks; labor unrest; Chinese politics; political stability; authoritarian regimes; strong states; export slowdown; shift-share instruments.

JEL codes: D73, D74, F10, F14, F16, H10, J52, P26

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1 Introduction

Negative economic shocks that adversely impact labor markets and the well-being of citizens often have repercussions for domestic political outcomes. The resulting citizen discontent can naturally translate into a decrease in support for the government, and in extreme cases, even trigger public unrest that threatens the stability of the incumbent. How then do political leaders respond to the domestic pressures that are likely to arise following such shocks?

This question is singularly prominent in the context of China, where it has regularly been posited that high rates of economic growth are crucial to the stability of the regime.[1] At the same time, we know relatively little about how the Chinese political system would respond to weak economic conditions, since its incumbents do not need to face voters, as in democracies, nor need they imminently fear being removed by popular uprisings, as in weakly institutionalized polities. Instead, China is a leading example of a non-democratic regime with relatively strong levels of state capacity. Understanding the political response of such regimes to negative economic shocks is of increasing relevance, not only because of the specific case of China, but also in light of the "democratic recession" that appears to have increased the number of authoritarian regimes around the world (Diamond 2015).[2]

We study this issue using the opportune setting afforded by the well-documented recent slowdown in China's export performance. While Chinese merchandize exports grew at a rapid average annual rate of 18% between 1992-2008 (Hanson 2012), this has gone into a sharp reversal since 2012 (see Figure 1). China's manufacturing exports registered an average annual growth rate of just 3.6% between 2013-2015, even slipping into a contraction for several years, in line with the weak performance of trade flows in the rest of the world since the global financial crisis.[3] Needless to say, the "tariff war" between the US and China triggered in 2017 has cast a further dampener on China's exports, raising the prospect of a protracted slowdown.

This has sparked concerns regarding the potential impact on labor markets and workers, given the prominent role that exports have played in driving China's economic development and employment since the early 1990s.[4] Indeed, as export manufacturing orders have declined,

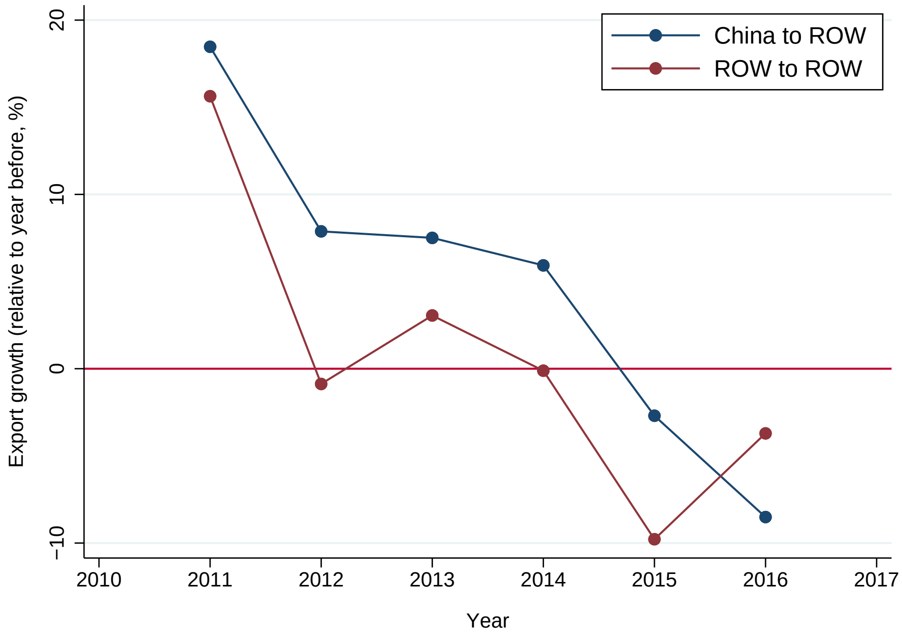
[1]As put by *The Economist* (1 Jun 2011): "The [Chinese] government cites stability as its source of legitimacy, and it draws a tight connection between stability and economic growth." Or, in the words of then-US Treasury Secretary Henry Paulson: "The Chinese see economic growth as essential to their stability" (Paulson 2008).

[2]Cases like Russia under Putin provide illustrations of the revival of strong-state authoritarianism. See Levitsky and Way (2015) though, for pushback on the extent of this democratic recession.

[3]Calculated from UN Comtrade data, as the average of the growth rates recorded in 2012-2013, 2013-2014, and 2014-2015. For comparison, the nominal value of manufacturing exports from the rest of the world to all destinations excluding China decreased during this same period at an average annual rate of -2.3%. Note that we refer to the time period of our study as 2013-2015, although it should be understood that data for 2012 and 2013 are used to calculate annual changes that we associate with 2013.

[4]As an illustration, in a State Council executive meeting on 21 Apr 2016, Premier Li Keqiang emphasized the need to stabilize China's exports amid the "harsh" foreign trade environment, as this was of concern not only to GDP, but also to a large volume of employment (http://www.gov.cn/xinwen/2016-04/21/content_5066423.htm). More formally, Feenstra and Hong (2010) have found that export growth accounted for employment growth of

Figure 1: Manufacturing Export Growth: China and the Rest of the World (ROW)



reports have emerged of a rise in layoffs and factory shutdowns; in several instances, factory managers were even alleged to have fled and absconded with company funds. This in turn has set off strikes over job losses and unpaid wage arrears.[5] While the labor grievances have each been localized in nature, the reports of these strikes have nevertheless been spread out geographically across China. This has led to concerns that the cumulation of such labor-related "events" could compromise domestic political stability.[6]

We present formal evidence, focusing on the period up to 2016, linking the slowdown in China's exports to a rise in incidents of labor unrest, using an empirical strategy that exploits the variation in the severity of the slowdown across localities and over time.[7] We then show how this prompted a set of systematic political responses, from local leaders as well as from the central government: The export slowdown heightened the attention and fiscal resources

7.5 million workers per year in China between 2000 and 2005. See also Los et al. (2015) for a related exercise that arrives at even larger estimates of the importance of exports for China's employment.

[5]To give but one example, several hundred workers reportedly staged a peaceful march on 30 April and 1 May 2015 along the streets of Dongguan prefecture, a major manufacturing hub in Guangdong province, when the apparel factory where they were employed shuttered overnight and the factory manager became untraceable (see https://www.rfa.org/mandarin/yataibaodao/renquanfazhi/yf1-05012015100541.html). Dongguan has been a particularly hard-hit prefecture during the export slowdown (*New York Times*, 20 Jan 2016). The assessment that incidents of labor unrest have been on the rise is consistent with media reporting (e.g., *New York Times*, 14 Mar 2016), as well as analysis by China political watchers (e.g., Tanner 2014).

[6]This is aptly captured in the following quote from Eli Friedman, a Cornell University scholar on Chinese labor relations: "This is probably the thing that keeps Xi Jinping up at night. Governments are not swimming in money the way they used to be, and there's less room to compromise" (*New York Times*, 14 Mar 2016).

[7]We conduct our analysis at the level of prefectures, a sub-provincial administrative unit. The analysis stops in 2016 due to limitations on the data on labor strikes thereafter (see Section 3.2), and also given the substantial change in the forces affecting China's exports following the start of the US-China "tariff war".

that local leaders devoted to enforcing public security on the ground. At the same time, we find that the central government held local leaders closely to account for their performance in maintaining stability, as reflected in decisions made over their retention or replacement.

To establish these points, we marshal a combination of both conventional and novel data sources. A key part of our contribution here is to overcome the challenge posed by the tight state control of news and information within China, in order to introduce systematic data at the local level on labor-related incidents and the government's response to these events.

The core data on labor strikes comes from a non-governmental organization (the China Labour Bulletin, CLB) that monitors developments on labor rights issues in mainland China. We establish a robust relationship from the slowdown in exports to a rise in the number of CLB-recorded labor strikes per worker, using a prefecture-level panel dataset of annual observations from 2013-2015. To support the claim that this relationship is causal in nature, we adopt a shift-share (or Bartik) instrumental variable (IV) for the severity of the export slowdown. This exploits the fact that prefectures differ in the initial product composition of their export baskets, which generates variation in how inherently exposed each prefecture would be to shocks to global trade flows across products (c.f., Autor et al. 2013).[8]

Our preferred IV specifications indicate that, were a given prefecture to experience a one-standard-deviation more severe contraction in exports, this would be associated with 0.27 more recorded labor events per million workers – a sizable effect, given that the median strike intensity in our dataset is 0.96. We confirm that this effect is driven by labor events in the manufacturing sector, and where the underlying cause recorded was "wage arrears". These findings are robust under a battery of sensitivity checks, including exercises that speak to recent Bartik IV best-practice recommendations, in terms of validating the case for causal identification (Goldsmith-Pinkham et al. 2018, Borusyak et al. 2018) and improving the statistical inference drawn (Adão et al. 2019). On a related note, we obtain a consistent picture of the adverse impact of the export shock when examining other contemporaneous economic outcome variables, such as the manufacturing employment share at the prefecture level.

On the political response, we start from the observation that there are phrases – most notably, "weiwen" ("维稳") or "maintaining social stability" – that have been adopted by the party establishment in China as watchwords to communicate the importance of domestic law and order as a political priority (*New York Times*, 2012). We undertake a textual analysis of prefecture work reports – an official speech delivered annually by the highest-ranking local party official (the party secretary) – to construct measures of the degree of "weiwen" emphasis in this

[8]Such shift-share IVs are valid to the extent that movements in rest-of-the-world trade flows are being driven by forces exogenous to developments in China. We draw support on this front from studies such as the 2016 IMF World Economic Outlook, which found that the world trade slowdown was accounted for largely by weak global demand, with supply-side forces and trade frictions playing smaller roles in comparison (Aslam et al. 2016). Moreover, our findings do not appear to be driven by shocks to domestic demand or output within China, when we seek to directly control for these using measures constructed at the prefecture level (see Section 5.2).

policy document. This includes a basic keyword count measure, as well as scores obtained from more sophisticated machine-learning algorithms, namely the Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM) methods, that have been used for the purposes of text classification. Using a similar shift-share identification strategy as above, we find that a more severe shock to a prefecture's exports is associated in the subsequent year with a discernible rise in the emphasis placed on "weiwen" in the annual work report.

We then show evidence of more concrete fiscal responses by local incumbents, using data on prefecture government expenditures collected from disparate statistical yearbooks. We establish that a more severe export slowdown led to a subsequent rise in expenditures channelled towards public security uses (consistent with a rise in the exercise of repression to bolster stability), as well as towards social spending (consistent with efforts to shore up public support). This fiscal response was stronger in prefectures that had seen larger increases in strikes in prior years, or where the local party secretary was younger; the latter finding in particular is consistent with such leaders having greater career concerns tied in with their performance in delivering stability. Interestingly, we detect evidence that prefectures with stronger initial fiscal capacity were less inclined to raise public security spending and more willing to expand social spending, suggesting that the latter measures require a more intensive use of fiscal resources.

Turning to the response of the central government, we examine patterns in the turnover of prefecture party secretaries, using information on career histories collected from their curricula vitae. We find that a more severe export shock raised the likelihood of incumbent turnover, specifically that he/she would be laterally re-assigned early in his/her tenure as party secretary, leaving a dent in his/her eventual promotion prospects. These turnover decisions moreover appear to be tied to the local official's performance in managing the labor situation on the ground in the shadow of the export slowdown: the party secretary was particularly likely to be replaced in prefectures that saw a high level of "excess strikes", namely in excess of the level of labor events that would be predicted from observed local economic conditions including the severity of the export shock.

These features are consistent with a simple model of "political accountability with Chinese characteristics" we develop, in which local officeholders can be removed by an upper-level government. The latter's goal is to identify and properly incentivize high-quality local agents to adopt measures that would bolster social stability. Given the observable nature of the export shocks we exploit in our empirical analysis, we assume that the upper-level government fully observes the (exogenous) shock that hits a given locality and the level of instability that ensues, but is imperfectly informed about the local incumbent's ability and the actions he/she adopted.

This framework helps to organize our set of findings on the political economy consequences of negative economic shocks in China and, more broadly, in nondemocratic strong states. Our model predicts that incumbents who have been hit by a negative economic shock face a greater likelihood of being replaced; this is not unlike what has been observed in both democracies or weak autocracies (see the literature review in Section 2 below). Where the strong autocracy is distinct, though, lies in the nature of how political "accountability" is exercised, namely within the system from above. We show that the distinction has meaningful implications: It entails for instance that in strong autocracies, it is the local officials with brighter career prospects who will mount stronger responses to bolster regime stability. Moreover, a key takeaway is that a central government seeking to properly incentivize local incumbents in the face of negative economic shocks would indeed assess them by a relative yardstick ("excess strikes"), rather than against an absolute standard (the level of strikes).

The paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes our main data sources, before Section 4 discusses the empirical strategy. Section 5 presents the findings on the effects of the export slowdown on labor strikes. Section 6 lays out a model linking export shocks, instability, and incumbent behavior. Sections 7 and 8 then report our empirical findings on measures to bolster domestic stability and on incumbent turnover. Section 9 concludes. Appendix A documents details related to the data, while Appendix B reports additional results and checks.

2 Related Literature

Our paper engages three strands in the literature. First and foremost, it connects with a broader set of studies on the political ramifications of negative economic shocks. In the context of democracies, it has been argued that an incumbent's response to such shocks can reveal information about his/her quality (e.g., Fearon 1999), and that the threat of electoral punishment for a bad response can be a powerful incentive that shapes incumbents' behavior (e.g., Barro 1973, Ferejohn 1986).[9] This has motivated an extensive body of empirical work on "economic voting", to examine whether voters do in fact hold politicians accountable for a weak economy at the ballot box (e.g., Lewis-Beck 1998, Duch and Stevenson 2008).[10]

On the other end of the spectrum, there is also a substantial literature on the impact of economic shocks in weakly institutionalized polities. Bad economic times are seen to reduce the opportunity cost of conflict, as well as generating dissatisfaction ("grievances") with incumbent performance, both of which can translate into anti-incumbent political action. In the context of weak states, such unrest can pose an immediate threat to the government of the day. Negative shocks have been linked to political instability (e.g., Haggard and Kaufman 1995, Alesina et al. 1996, Burke 2012), conflict (e.g., Miguel et al. 2004, Hendrix and Salehyan 2012, Bazzi and

[9] The systematic manner in which economic conditions can influence incumbents' decisions would also raise the possibility of political business cycles (see Persson and Tabellini 2000).

[10] It has been further argued that the nature of the relationship between economic weakness and voting patterns would vary depending on the presence of an independent media (Besley and Burgess 2002), on other local institutions (van der Brug et al. 2007), and on culture (Nunn et al. 2018). See also Healy et al. (2017) who examine data on the motivations that drive economic voting at the individual level.

Blattman 2014), coups (e.g., Dube and Vargas 2013, Kim 2016), and even democratic change (e.g., Burke and Leigh 2010, Brückner and Ciccone 2011).[11]

Less is known, however, about contexts in which governments are authoritarian, and thus need not worry about electoral accountability, yet are sufficiently stable that they do not face an immediate existential threat. The role of social protest in the Chinese system has been investigated in its many facets (e.g., Chen 2012), but as far as we are aware, without a systematic quantitative assessment of the impact on incumbent behavior. Related to this, Lorentzen (2013) has argued that protest in China, far from signaling regime weakness, is actually used as an information extraction device by higher levels of government. Our findings are consistent with this view, and moreover suggest that the higher-level decision-makers are fairly sophisticated, in that they appear to draw a distinction in their evaluation of local leaders between incumbent performance and the impact of negative shocks beyond the incumbent's control. This contrasts with the evidence uncovered from democracies, where voters have been shown to mis-attribute negative economic shocks to poor performance, and thus end up voting out the incumbent for what amounts to bad luck (see the survey by Healy and Malhotra 2013).[12]

Our paper relates to a second strand of literature on the labor market and worker effects of exposure to international trade, on which we draw in our use of a shift-share IV strategy. While many of these existing studies have focused on the consequences of an increase in exposure to imports (Topalova 2010, Autor et al. 2013, Acemoglu et al. 2016, Dix-Carneiro and Kovak 2017, Dix-Carneiro et al. 2018, etc.), we instead study the effects that shocks to export opportunities can have on a key developing country.[13] Along these lines, we also contribute to a body of work that has explored how exposure to trade has affected political outcomes, including legislative voting (Feingenbaum and Hall 2015), electoral voting (Jensen et al. 2017, Che et al. 2018), political polarization (Autor et al. 2017), support for extremist parties (Dippel et al. 2018), and support for cross-border economic integration (Colantone and Stanig 2018).

Last but not least, our study is related to the literature on China's political system, specifically the management of its cadres. The existing work has identified several key determinants of promotion within this system, including local economic performance (Li and Zhou 2015), political connections (Jia et al. 2015), social ties (Fisman et al. 2015), and factions (Francois et al. 2016, Shih and Lee 2018). We complement these studies by showing that an official's relative performance in maintaining social stability can be a crucial determinant for his/her career prospects. Persson and Zhuravskaya (2016) and Chen and Kung (2016, 2018) have moreover shown that the career concerns of Chinese politicians has swayed public spending towards uses

[11] Interestingly, this link from economic setbacks to civil conflict has been studied for several historical episodes in China when state institutions were weaker (see Jia 2014, Braggion et al. 2018).

[12] For specific examples, see Achen and Bartels (2004), Leigh (2009), and Cole et al. (2012), as well as the discussion between Achen and Bartels (2018) and Fowler and Hall (2018).

[13] See McCaig (2011) for an exception in this regard, that explores how Vietnam's entry into export markets affected poverty at the provincial level.

that deliver a short-term boost to economic growth (such as construction projects). We find related evidence that economic shocks can induce a shift in fiscal resources towards uses aimed at bolstering social stability.

3 Data Sources and Measures

We turn now to our empirical setting and key data sources. We describe in this section the data we use to first establish a relationship between the slowdown in exports and labor strikes, while postponing a discussion of the measures of political response and turnover to Sections 7-8. Further details about the data construction are provided in Appendix A.

The unit of analysis throughout this paper is the prefecture, this being the division below the level of the province within China's administrative hierarchy. We include all prefectures across China, except Tibet due to data limitations. There are 333 prefectures in our sample, with a median land area of 12,980km^2 and a median population of 3.25 million in 2010.[14]

3.1 Exports

We focus on the performance of manufacturing exports as our key local economic shock variable. For this, we draw on China's General Administration of Customs, which covers the universe of China's exporters and importers. For each trading firm, the customs data provides information on its location and a breakdown of its trade flows at the Harmonized System (HS) 6-digit product level. We aggregate across all firms f located in prefecture i to construct a measure of manufacturing exports per worker in year t:

$$Export_{it} = \sum_k \sum_{f \in i} \frac{X_{fikt}}{L_{i,2010}}. \tag{1}$$

Note that k indexes HS 6-digit codes, and we include all products k that map to the manufacturing sector.[15] $L_{i,2010}$ denotes the working-age population (ages 15 to 64) in prefecture i and year 2010; this data are from the China Population Census, and includes all individuals both with or without residency rights (hukou). We will consider the annual change in exports – defined as $ExpShock_{it} = Export_{it} - Export_{i,t-1}$ – as our main explanatory variable; by construction, this measures the change in manufacturing exports in 1000 USD per worker. Our regression analysis will be based on a panel that covers the period $t \in \{2013, 2014, 2015\}$. We avoid the years prior to 2012, since this overlaps with the trade collapse and subsequent recovery from

[14] While there have been some changes to administrative boundaries over time, we have constructed all our variables to be in accord with the 2010 administrative divisions.

[15] We use all HS product codes that map to SIC manufacturing industries, namely SIC industries with leading digit equal to 2 or 3. The mapping to SIC is from the World Integrated Trade Solutions (WITS) at: https://wits.worldbank.org/product_concordance.html.

the global financial crisis. Our findings continue to hold if we were to extend the sample to include the export shock between 2015-2016 (available on request), but we do not use any more recent years as forces related to the US-China "tariff war" would come into play.

Figure 2: Prefecture-Level Annual Export Growth Rates
(Tail 5% top- and bottom-coded within each year)

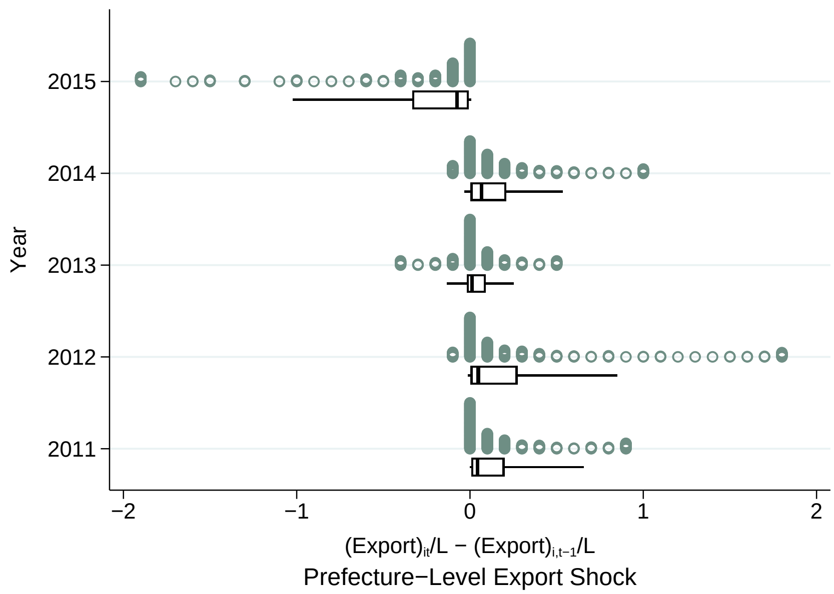


Figure 2 shows the distribution of $ExpShock_{it}$ across prefectures in the years leading up to 2015.[16] There is considerable spatial and temporal variation in the per worker export shock. The export slowdown was particularly marked in 2015, with a mean decline across prefectures of 372 USD per worker from the year before. More importantly, there was substantial variation in the severity of the export shock; in 2015, for example, the standard deviation of $ExpShock_{it}$ across prefectures was 948 USD per worker (see the summary statistics in Panel A of Table 1).

We will later verify the robustness of the results to using alternative export shock variables, such as when excluding firms that are pure intermediaries, or when focusing on exports by firm ownership types (e.g., privately-owned versus state-owned enterprises), these being distinctions that are relevant in the context of China's export activities. Likewise, our findings continue to hold when we work with an export shock variable that is constructed as an export growth rate (rather than as a dollar value change).

3.2 Labor strikes

Given the authoritarian nature of the political regime, it may come as a surprise that labor strikes even occur in China. In reality, collective actions and strikes are a fixture of China's

[16]For the purposes of this figure, the data have been top- and bottom-coded at the 5th and 95th percentile values respectively across prefectures in any given year. Given the long tails in the export shock measure, we take care to verify in the later regression analysis that our results are not driven by potential outliers.

Table 1: Summary Statistics

Panel A: Labor Strikes and Economic Variables	2013	2014	2015	All Years
Δ Number of CLB events per million workers	0.208	0.742	1.239	0.730
	(0.647)	(1.075)	(1.769)	(1.320)
Export Shock (1000 USD per worker)	0.016	0.233	-0.372	-0.041
	(0.547)	(0.755)	(0.948)	(0.806)
Export Shock, Bartik IV (1000 USD per worker)	0.171	0.093	-0.659	-0.132
	(0.532)	(0.371)	(1.374)	(0.953)
Δ Log College-enrolled share of population	0.039	0.049	0.046	0.045
	(0.150)	(0.172)	(0.136)	(0.154)
Δ Log Mobile share of population	0.080	0.030	-0.004	0.035
	(0.110)	(0.085)	(0.097)	(0.104)
Δ Log Internet share of population	0.140	0.105	0.108	0.117
	(0.208)	(0.199)	(0.159)	(0.190)
Δ Log Average wage	0.096	0.080	0.103	0.093
	(0.068)	(0.051)	(0.065)	(0.062)
Δ Employment / Population	0.034	-0.010	0.000	0.008
	(0.192)	(0.180)	(0.021)	(0.153)
Δ Manufacturing employment / Population	0.011	-0.001	-0.001	0.003
	(0.069)	(0.007)	(0.009)	(0.041)
Δ Log Industrial output per capita	0.121	0.065	-0.008	0.059
	(0.097)	(0.193)	(0.220)	(0.186)
Panel B: Political Economy Response Measures	**2014**	**2015**	**2016**	**All Years**
Δ "weiwen" keyword	-0.007	0.007	-0.011	-0.004
	(0.042)	(0.047)	(0.040)	(0.043)
Δ Log "weiwen" score, MNB	-0.059	0.198	-0.426	-0.097
	(0.816)	(0.753)	(0.844)	(0.845)
Δ Log "weiwen" score, SVM	-0.090	-0.087	-0.271	-0.150
	(1.220)	(1.160)	(1.312)	(1.234)
Δ Log fiscal expenditure, Public security	0.050	0.114	0.128	0.097
	(0.083)	(0.110)	(0.118)	(0.110)
Δ Log fiscal expenditure, Social spending	0.077	0.134	0.080	0.098
	(0.074)	(0.080)	(0.074)	(0.080)
Δ Log fiscal expenditure, Total	0.077	0.136	0.066	0.093
	(0.067)	(0.114)	(0.075)	(0.093)
Party secretary Turnover	0.131	0.322	0.435	0.296
	(0.338)	(0.468)	(0.496)	(0.457)
Party secretary Turnover, Lateral	0.046	0.164	0.280	0.163
	(0.209)	(0.371)	(0.450)	(0.370)
Party secretary Turnover, Early lateral	0.024	0.067	0.061	0.051
	(0.154)	(0.250)	(0.239)	(0.219)

Notes: All annual changes are computed relative to the previous year. The mean across prefectures (excluding Tibet) is reported, with the standard deviation in parentheses. The "All Years" column reports the summary statistics pooled across all years and prefectures in the prior columns. The Δ Log College-enrolled share through Δ Log Industrial output per capita variables are computed from the annual City Statistical Yearbooks. The construction of the textual analysis measures, fiscal expenditure variables, and party secretary turnover records are described in Sections 7.1, 7.2, and 8 respectively.

industrial relations landscape, as workers often see this as the only effective avenue for recourse over employment grievances.[17]

We use data on labor strikes drawn from the China Labour Bulletin (CLB), a non-profit organization based in Hong Kong which has monitored and logged incidents of collective worker actions across mainland China since 2011. Up until 2017, the CLB gathered this information on a daily basis from online and media sources, including but not limited to Sina Weibo, WeChat, Tianya, Baidu, and Google.[18] In the absence of official statistics on strikes, this data hosted on the CLB Strike Map have been used regularly by news media outside of China to examine trends in worker actions within China.[19]

For each labor event, the CLB records the date, location (at the prefecture level), and a short description of the incident. For the vast majority of observations (>98%), the CLB further records: (i) the broad sector in which the worker action occurred (e.g., manufacturing, construction, services); and (ii) the underlying cause (e.g., wage arrears, layoffs, work conditions). A total of 5,156 labor events were recorded over 2012-2015, with most of these occurring in the manufacturing sector (36%), followed by construction (26%). The most common cause cited – in about 60% of the cases – was employee demands over wage arrears. For about one-third of the observations, the CLB description provides a brief account of how the worker action concluded. These accounts point to substantial unevenness across China in the manner in which local authorities managed the labor strikes in practice: the responses seen span the spectrum, from repression of the worker action (e.g., police arrests, use of pepper spray), to attempts at accommodation (e.g., mediation, negotiation, or even compensation).[20]

Figure 3 illustrates the distribution of CLB-recorded labor events across China during 2012-2015. As is clear from this map, the labor events are spread out geographically, even while the density of events appears to be higher in coastal manufacturing hubs such as the Yangtze River Delta and the Pearl River Delta. The summary statistics in Table 1 point to an increase over time in the occurrence of strikes, as measured by the number of labor events per million workers (with the denominator proxied by the age 15-64 population in the 2010 Census). While the average prefecture experienced an increase in strikes per million workers of 1.24 between 2014-2015, the cross-prefecture standard deviation in this change was also large (1.77).

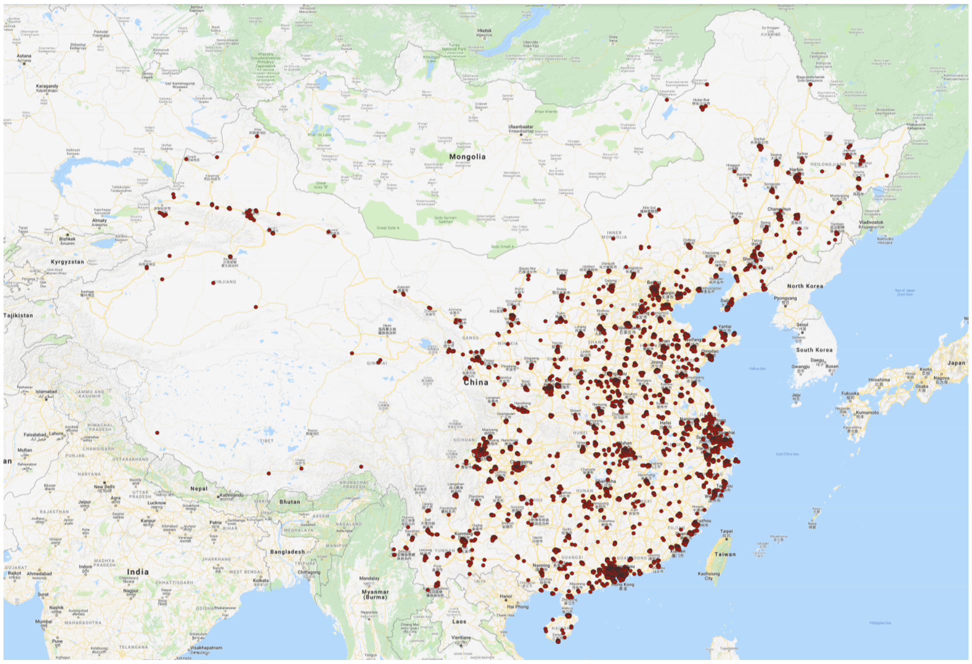
[17] For more background information on labor relations in China, see: https://clb.org.hk/content/labour-relations-china-some-frequently-asked-questions.

[18] Starting in 2017, the CLB switched to updating on a weekly or twice-weekly basis, which limits the comparability of the data pre- and post-2017. This is another reason for focusing our analysis on the period prior to 2017.

[19] See for example, the *Financial Times* (14 July 2016): https://www.ft.com/content/56afb47c-23fd-3bcd-a19f-bddab6a27883; *The Economist* (19 March 2016): https://www.economist.com/china/2016/03/19/deep-in-a-pit; and *The New York Times* (14 March 2016): https://www.nytimes.com/2016/03/15/world/asia/china-labor-strike-protest.html. The CLB Strike Map data is at: https://maps.clb.org.hk/strikes/en. See Qin et al. (2019) for another recent paper that uses the CLB data, specifically to understand the diffusion of strikes.

[20] Of the 5,156 observations from 2012-2015, the CLB records indicate that police were involved and arrests made in 1,415 cases, while mediation and negotiation (without any arrests) was the outcome in 396 cases.

Figure 3: CLB Map (2012-2015)



Given the manner in which the data are collected, the CLB are careful to acknowledge that they do not have a complete record of all labor incidents. For our empirical analysis though, what will be more crucial is whether the CLB data are adequately picking up trends over time and across locations in the occurrence of labor strikes. To corroborate as best we can this dimension of the data, we have compared the CLB data against official records on the number of labor dispute cases submitted for mediation or arbitration, as reported in the China Labor Statistical Yearbooks published by the Ministry of Human Resources and Social Security (MOHRSS). While this MOHRSS data is only available at the more aggregate province level (and hence not ideal for our regression analysis), we nevertheless view it as a useful measure of the frequency of labor disputes against which we can cross-check the CLB data.

Panel A of Figure A.1 plots the number of CLB labor events and MOHRSS labor disputes aggregated at the national level, expressed in terms of events per million workers (see Appendix A.1).[21] Note that the total number of CLB events (right vertical axis) is smaller than the total number of MOHRSS labor disputes (left vertical axis). This could be due to strikes being a more extreme and hence less frequent form of worker action; alternatively, this could simply reflect that the CLB do not capture all significant labor events that have taken place. Notwithstanding the difference in scale, the CLB strike data clearly follow a similar upward trend as the MOHRSS records; this is true both in levels (Panel A) or in annual changes (Panel B). Panel C further compares the annual changes in these two variables across provinces p and

[21] We use the total number of labor dispute cases raised either collectively or by individuals; a very similar set of cross-check results is obtained when dropping the labor disputes raised by individuals.

years t ($t \in \{2013, 2014, 2015\}$). This confirms that annual changes in the number of CLB-recorded strikes per million workers are positively correlated with the corresponding changes in MOHRSS-recorded labor disputes per million workers.

A more subtle concern is that the intensity of reporting on labor unrest could vary systematically with the extent of the economic shock experienced in a location. This would be a source of nonclassical measurement error that could lead to a spurious negative correlation between the number of CLB strikes and the change in exports, if internet sources were to intensify their efforts to report on labor unrest in locations where the export shock was more severe. Conversely, the reporting of labor disputes in the MOHRSS for such locations might have actually declined, if local officials there had a greater incentive to discourage the filing of labor disputes. We investigate this possibility by comparing the ratio of the number of CLB to MOHRSS events, $Events_{pt}^{CLB}/Events_{pt}^{MOHRSS}$, against the observed change in the value of exports per worker, where the latter are constructed using the analogue of (1) at the province level. The correlation coefficient between these two variables turns out to be small (0.0032) and not statistically significant.[22] While we are unable to conduct a similar analysis at the prefecture level due to data limitations, we take the above check as reassuring that such forms of systematic reporting bias are unlikely to be prevalent in the data.

3.3 Other Local Economic Data

We also collected a set of socioeconomic variables at the prefecture level to be used as controls or as additional local economic outcomes to be explored. These were obtained from various official or public data sources; summary statistics for a selection of these variables are included in Panel A of Table 1.

Data on the working age population and the population breakdown by migration status (hukou vs non-hukou) were drawn from the 2010 Population Census. Data on other economic variables – such as the average wage level, gross industrial output per capita, manufacturing employment share of the population, college educated share of the population, mobile and internet penetration rates – were computed from the China City Statistical Yearbooks. Note that these Yearbooks report only on urban prefectures, which reduces our coverage to 290 prefectures when these latter variables are used. That said, this is the best publicly-available source (as far as we are aware) that provides annual prefecture-level data. Last but not least, we have supplemented the above with a commonly-used proxy for economic activity based on night-lights intensity, constructed from the Visible Infrared Imaging Radiometer Suite Day/Night Band dataset (see Appendix A.2 for more details).

[22] The correlation between the annual change in this ratio of CLB to MOHRSS events and the province-level export shock is likewise small (0.0384) and statistically not significant.

4 Empirical Strategy

In this section, we elaborate on the regression model and identification strategy that we adopt to uncover the effects of the export slowdown on incidents of labor strikes. This forms the first piece of evidence in our discussion of broader political economy outcomes in China.

4.1 Estimating Equation

Our baseline regression specification is as follows:

$$\Delta(Event/L)_{it} = \beta_1 ExpShock_{it} + \beta_2 (Event/L)_{i,t-1} + \beta_X X_{it} + D_{pt} + D_i + \varepsilon_{it}, \qquad (2)$$

where i denotes prefecture and t denotes year. The dependent variable $\Delta(Event/L)_{it}$ is the change in number of CLB-recorded labor events per million workers, while the key explanatory variable $ExpShock_{it}$ is the change in manufacturing exports per worker previously defined in (1); both of these variables are constructed as changes between year $t-1$ and t. The regression stacks the first differences of three periods, 2012-2013, 2013-2014, and 2014-2015, and includes province-by-year dummies, D_{pt}, and prefecture dummies, D_i. The first-differencing removes any time-invariant determinants of labor unrest that are specific to each prefecture. The D_{pt} and D_i further account for any province-specific shocks across different time periods, as well as any prefecture-specific linear time trends in strike intensity, respectively. As a result, the coefficient β_1 is being identified off variation in export shifts across prefectures within provinces, as well as within prefectures over time.[23]

The X_{it} term refers to a set of time-varying prefecture characteristics which we control for as potential alternative determinants of labor strikes. We also include the lagged number of CLB events per worker $(Event/L)_{i,t-1}$, to capture any tendency towards mean reversion in the occurrence of strikes; our findings are similar even if we were to drop this variable (see Table B.1). We cluster the standard errors by province to accommodate the possibility of unobserved correlated shocks across prefectures within a given provincial unit.[24] In practice, we run the regressions weighting each observation by the working-age population in 2010, although this is not material for our results (see Table B.1).

[23]We express the labor strike variable in per million worker terms, to normalize the measure to a reasonable scale. Note though that this is not material for our findings: We continue to obtain a negative and significant β_1 coefficient if we were to instead replace $\Delta(Event/L)_{it}$ and $(Event/L)_{i,t-1}$ in (2) by $\Delta(Event)_{it}$ and $(Event)_{i,t-1}$ respectively (available on request).

[24]In Table B.8, we demonstrate that the findings continue to hold under alternative clustering schemes that seek to account for the concern in Adão et al. (2019), namely that the regression error terms could be correlated across prefectures that feature a similar initial export product mix, yet are not geographically proximate.

4.2 Instrumental Variable

An immediate concern with ordinary least-squares estimates of (2) is the issue of reverse causality, namely that it could instead be the occurrence of labor strikes that is adversely affecting export performance. We therefore construct a shift-share or Bartik IV for the export shock variable, to make a clearer case for a causal relationship running from a slowdown in exports to a rise in strikes. This IV combines information on the initial export mix within Chinese prefectures together with product-level shifts in world trade flows excluding China (henceforth, referred to as the "rest of the world" or ROW). To be more specific, we construct the following IV for $ExpShock_{it}$:

$$ExpShockROW_{it} = \sum_k \frac{X_{ik,2010}}{\sum_i X_{ik,2010}} \frac{\Delta X_{kt}^{ROW}}{L_{i,2000}}. \tag{3}$$

In the above, $\Delta X_{kt}^{ROW} \equiv X_{kt}^{ROW} - X_{k,t-1}^{ROW}$ is the change in product-k trade flows from the ROW to the ROW, based on HS 6-digit product-level data from UN Comtrade. Each product-k shift is apportioned to prefectures within China using weights $X_{ik,2010}/\sum_i X_{ik,2010}$ that reflect the importance of each prefecture i as an exporter of product k in a pre-sample year (2010), as constructed from the Chinese customs data. We express the IV in units of 1000 USD per worker, by dividing by the prefecture working-age population in the 2000 Census, $L_{i,2000}$; we use data from an earlier census since using the same denominator as in the construction of $ExpShock_{it}$ might artificially boost the first-stage correlation of the IV.

The validity of (3) as an instrument rests on the assumption that, conditional on the province-year and prefecture fixed effects, $ExpShockROW_{it}$ is uncorrelated with other time-varying, prefecture-specific determinants of the outcome variable that would be captured in the regression residual, ε_{it}, in (2). Given the Bartik-style construction, one would need to be reassured that the ε_{it} are uncorrelated with: (i) the initial export structure of the prefecture, and (ii) the product-specific export shocks observed at the national level. With regard to (i), a natural concern is that the initial export structure might directly drive prefecture-specific trends in labor strikes per capita. The inclusion of the D_i fixed effects helps precisely to guard against this concern, to the extent that the underlying trends are linear in nature.[25]

With regard to (ii), we view the rest-of-the-world trade shifts, ΔX_{kt}^{ROW}, as primarily picking up demand shocks that are external to China. This is supported by studies such as the IMF World Economic Outlook (Aslam et al. 2016), which found that about 60-80% of the global trade slowdown during this period was attributable to demand-side forces, specifically the weak recovery in world demand after the global financial crisis; these conclusions were reached via two separate methodologies, namely a reduced-form regression analysis and a model-based

[25]See for example McCaig (2011), who differences his outcome variable relative to pre-shock data to address this issue of confounding location-specific time trends that could be correlated with initial industry composition. With the inclusion of prefecture fixed effects, our empirical strategy is similar to his.

structural decomposition.[26] In comparison, supply-side forces and increases in trade frictions played a smaller role. In our present empirical context, what this means is that the shift-share IV we construct plausibly leverages on sources of variation in world trade flows that are driven by foreign demand conditions, and then projects these onto each prefecture on the basis of pre-determined product weights.

While (3) serves as our baseline IV, we will explore alternative constructions to further isolate variation in the ROW product-level trade flows that is driven by foreign demand forces. This includes measures that will seek to filter out demand shifts in foreign markets via a gravity-equation approach. We are also cognizant that the ΔX_{kt}^{ROW} terms might be incidentally correlated with domestic demand or domestic supply shocks stemming from within China, and so will report robustness results in which we make an effort to control for these latter forces. (We defer a more detailed discussion of these and other checks to Section 5.2.)

It is helpful at this juncture to discuss how the manner of construction of the IV in (3) compares with the empirical approach in Autor et al. (2013). Our application studies the effects of export shocks, rather than a shock to import competition. In addition, we adopt export shares ($X_{ik,2010}/\sum_i X_{ik,2010}$) when building our instrument, instead of analogous employment share weights as in Autor et al. (2013). As shown in Appendix A.3, the export shock defined in equation (3) that uses export-share weights can be rationalized by log-linearizing the relationship between exports and external demand shifts. Moreover, if one were to instead apportion the export shocks ΔX_{kt}^{ROW} on the basis of employment shares, this could systematically over-state the importance of export exposure in prefectures that are on the whole less export-oriented, such as China's inland provinces.

5 Effects of Export Shocks on Labor Strikes

We now present our core findings on the effect of the export slowdown on labor strikes at the prefecture level (Section 5.1). We include in this section a discussion of robustness checks and validation exercises for the Bartik IV strategy (Section 5.2), as well as corroborating evidence drawing on available data on other labor market and economic outcomes (Section 5.3).

5.1 Baseline Results

Table 2 reports our baseline results. Column 1 presents the OLS estimates of the specification in equation (2), revealing that an export slowdown (i.e., a more negative $ExpShock_{it}$) was indeed

[26] The regression-based analysis estimated an import demand system, which delivered the 80% headline number for the contribution of aggregate demand forces to the global trade slowdown. On the other hand, the model-based decomposition built off the multi-country model of production and trade of Eaton et al. (2016); this approach yielded a 60% figure for the contribution of aggregate demand forces to the decline in trade as a share of world GDP.

Table 2: Export Shocks and Labor Strikes

Dependent variable:	Δ **CLB Events per million**$_{it}$			
	(1) OLS	(2) IV	(3) IV	(4) OLS-RF
ExpShock$_{it}$	-0.1603***	-0.3190***	-0.3207***	
	(0.0327)	(0.0560)	(0.0539)	
ExpShockROW$_{it}$				-0.2002***
				(0.0324)
Events per million workers$_{i,t-1}$	-0.9167***	-0.9169***	-1.0027***	-1.0935***
	(0.1608)	(0.1792)	(0.1610)	(0.1123)
Δ Log College-enrolled share$_{it}$			0.2623	0.2437
			(0.1887)	(0.1997)
Δ Log Mobile share$_{it}$			1.4753*	0.7634
			(0.7353)	(0.6254)
Δ Log Internet share$_{it}$			0.3462***	0.5363***
			(0.1184)	(0.1591)
Prefecture dummies?	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y
First-stage F-stat	–	49.20	69.74	–
Observations	987	987	822	822
R^2	0.6234	0.6105	0.6464	0.6719

Notes: The dependent variable is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t. All regressions are weighted by the prefecture's working-age population in 2010. Column 1 reports OLS estimates, while Columns 2-3 are IV regressions. Column 4 reports the reduced-form where the Bartik IV is used directly in place of $ExpShock_{it}$ in an OLS regression. The additional control variables in Columns 3-4 are constructed as changes in log shares relative to prefecture population size, where the changes are taken between year $t-1$ and t. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

associated with a rise in CLB-recorded labor events per worker. We proceed to instrument in Column 2 for the export shock using the shift-share variable defined in (3).[27] The IV estimate points to a negative and statistically significant effect of the export shock in raising the occurrence of strikes, that is moreover larger in magnitude than the OLS estimate. This could be due to the standard attenuation bias arising from measurement error in the export shock variable. Alternatively, the OLS estimate in Column 1 may have been subject to omitted variables bias; for example, unobserved supply shocks due to automation could boost exports while also inducing more labor unrest from displaced workers, which would dampen the magnitude of the export shock coefficient, β_1. To the extent that the Bartik IV satisfies the exclusion restriction, it would leverage a component of $ExpShock_{it}$ that is orthogonal to such supply shocks to yield an estimate of β_1 that is not confounded by such forces.

We incorporate in Column 3 a set of concurrent socioeconomic shifts that could indepen-

[27]Although we do not report the estimates to save space, the shift-share IV is indeed positively correlated with the export shock. The table does report the F-stats; these are all in excess of the rule-of-thumb value of 10, confirming the relevance of the instrument for explaining the variation in $ExpShock_{it}$.

dently affect labor unrest. We control for the change in the log college-enrolled share of the general population, motivated by related work that has shown that individuals with higher levels of education have a greater propensity to engage in civic and even protest actions (see for example, Campante and Chor 2012). We further include the contemporaneous changes in the shares of mobile phone and internet subscribers in the prefecture population, to account for the diffusion of digital information and communication technology (ICT) and its potential role in facilitating the mobilization of workers (Manacorda and Tesei 2016, Campante et al. 2018).[28] These control variables each exhibit a positive correlation with the occurrence of labor strikes, with the role of broader access to ICT even being statistically significant.[29] That said, the estimated effect of the export shock on increases in strikes remains stable when these further controls are used. Lastly, Column 4 reports the reduced-form effect of our shift-share variable on strike intensity in an OLS regression, to confirm that a decrease in the ROW export shock is directly relevant for explaining a rise in incidents of labor unrest.

To gauge the magnitude of the implied effects, consider the differential change in strike intensity that would be induced by a one standard deviation shift in the export shock (about \$841 per worker in the Column 3 regression sample). The β_1 point estimate from Column 3 translates this into 0.27 more strike events per million workers, which is sizeable considering that the median occurrence of strikes in our sample is 0.96 per million workers.

We explore next the nature and causes of these labor strikes. Making use of the breakdown of these labor events by broad sector, Table 3 confirms that the observed effect on labor strikes was concentrated in the manufacturing sector (Column 1). Note that we run IV regressions in this table following the specification in Column 3 of Table 2, but use instead as the dependent variable the annual change in labor events in the respective sector (normalized by the 2010 prefecture working age population); when we do so, we also use a sector-specific measure of $(Event/L)_{i,t-1}$ on the right-hand side.[30] Bearing in mind that $ExpShock_{it}$ was constructed from manufacturing product trade flows, this finding verifies that the manufacturing sector did indeed bear the brunt of the labor market fallout. This also affected workers in construction and services (Columns 2 and 5), albeit with smaller estimated effects. On the other hand, the export slowdown was not systematically linked with labor unrest in the mining or transportation sectors (Columns 3 and 4).[31]

[28]These variables would also help to control for differences across prefectures in the likelihood that a given labor strike might be recorded by the CLB, to the extent that such differences in reporting intensity are related to variation in the prevalence of ICT.

[29]These auxiliary control variables are constructed as changes between year $t-1$ and t (i.e., contemporaneous with the dependent variable). A natural concern is that education and ICT usage may themselves be outcomes affected by the export shock; we should stress though that our conclusions on the effect of the export shock on labor strikes and other political outcomes remain robust even if we were to drop these auxiliary controls (see Table B.1).

[30]The five sectors considered in Table 3 account for about 90% of all CLB labor incidents. The sectors omitted from the table are "Education", "Retail", and "Others".

[31]There are two possible explanations for the larger spillover effects of the export shock on construction and

Table 3: Export Shocks and Labor Strikes: By Sector

Dependent variable:	Δ **CLB Events per million**$_{it}$				
Sector:	**Manufacturing**	**Construction**	**Mining**	**Transportation**	**Services**
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
ExpShock$_{it}$	-0.1609***	-0.1104***	0.0062	0.0119	-0.0423***
	(0.0202)	(0.0321)	(0.0074)	(0.0254)	(0.0124)
Events per million workers$_{i,t-1}$	-0.8822***	-0.8231***	-1.1368***	-1.4104***	-1.3641***
	(0.1445)	(0.2366)	(0.1878)	(0.0576)	(0.0853)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	45.74	134.6	104.6	134.5	95.64
Observations	822	822	822	822	822
R^2	0.6424	0.6267	0.5375	0.7008	0.6543

Notes: The dependent variable is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, that occurred in the sector in question; the "Events per million workers$_{i,t-1}$" variable is the corresponding sector-specific level of CLB events per worker at time $t-1$. All columns report IV regressions, weighted by the prefecture's working-age population in 2010. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 further exploits the available information on the reported causes of the labor events. We consider three categories of employee demands, arising from: (i) wage arrears; (ii) wage arrears and/or layoffs; and (iii) all other causes (*not* wage arrears or layoffs, which includes as an example disputes over work conditions).[32] Using an IV specification analogous to that in Table 3, the regressions in Table 4 confirm that negative export shocks prompted an increase in labor strikes over wage arrears (Column 1), with an even larger estimated effect if strikes related to layoffs are also considered (Column 2). By contrast, we find no statistically significant effect of $ExpShock_{it}$ on labor events from other residual causes (Column 3). We obtain a similar set of findings when restricting the event counts only to strikes that occurred in the manufacturing sector: While we now find a significant effect on labor events associated with residual causes (Column 5), this effect is much smaller in magnitude compared to the rise in strikes over wage arrears or layoffs (Column 4). Viewed together, Tables 3 and 4 paint a consistent picture, that the negative shock to the manufacturing sector led to a rise in expressions of worker distress over unpaid wages or layoffs.

In Table 5, we look into several additional facets of the prefecture export shock variable.

services. First, the skills developed in the manufacturing sector could be less directly transferable to jobs in mining and transportation. Second, the state plays a relatively larger role in mining and transportation, and so could provide more of a buffer to cushion workers in these sectors from negative shocks. For example, according to China's 2013 Economic Census, the share of employment by state-owned enterprises (SOEs) was only 4.7% in the construction sector, while the corresponding employment share was 27.5% for the transportation sector.

[32] Where multiple causes were cited for an event, we counted the incident as being about "wage arrears" (respectively, "layoffs") if the term appeared anywhere in the list of recorded employee demands.

Table 4: Export Shocks and Labor Strikes: By Causes

Dependent variable:	Δ **CLB Events per million$_{it}$**				
Cause:	**Wage Arrears**	**Wage Arrears and Layoffs**	**NOT Wage Arrears and Layoffs**	**Wage Arrears and Layoffs**	**NOT Wage Arrears and Layoffs**
Sector:	All	All	All	Mfg.	Mfg.
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
ExpShock$_{it}$	-0.3532***	-1.6156***	0.1116	-1.5647***	-0.1756***
	(0.0634)	(0.3574)	(0.0789)	(0.3576)	(0.0383)
Events per million workers$_{i,t-1}$	-0.6130***	-0.5709	-1.3832***	-0.6583	-1.0932***
	(0.1785)	(0.5130)	(0.0955)	(0.4441)	(0.1424)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	84.37	31.14	128.9	31.87	65.29
Observations	822	822	822	822	822
R^2	0.6312	0.5320	0.7149	0.5334	0.6713

Notes: The dependent variable is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, for which the recorded cause is as indicated in the column heading; Columns 1-3 include events across all sectors, while Columns 4-5 include only events that occurred in the manufacturing sector. The "Events per million workers$_{i,t-1}$" variable is the corresponding economy-wide or manufacturing-specific level of CLB events per worker by recorded cause at time $t-1$. All columns report IV regressions, weighted by the prefecture's working-age population in 2010. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Column 1 considers whether spatial correlation in the export shock across prefectures might confound the interpretation of our findings. To address this, we construct the working-age population-weighted average of $ExpShock$ across all prefectures that share an administrative border with i; when we include this as a right-hand side variable, we further instrument for it with an analogous neighboring-prefecture weighted-average measure of $ExpShockROW$. While the estimates in Column 1 point to interesting evidence of spillovers from shocks in neighboring prefectures, the local export shock remains important for explaining the rise in labor incidents in prefecture i itself. In Column 2, we examine if the time-$(t+1)$ export shock might have explanatory power for the incidence of strikes at time t, by replacing the contemporaneous export shock variable in (2) with $ExpShock_{i,t+1}$, and instrumenting for it with the time-$(t+1)$ Bartik variable. Compared to the baseline results in Column 3 of Table 2, the export shock coefficient is smaller in magnitude and statistically insignificant. This helps to allay the concern that our results could be driven by pre-determined trends in the evolution of exports at the prefecture level, that are in turn spuriously correlated with labor market outcomes.

Motivated by the anecdotal reports of factory closures, we examine in Column 3 whether the rise in labor incidents can be linked to firm exit induced by the slowdown in exports. To do so, we split $ExpShock_{it}$ into a component that reflects firm exit from exporting – defined here as firms that record positive exports in the customs data (in year $t-1$), but cease to

Table 5: Export Shocks and Labor Strikes: Heterogeneous Effects

Dependent variable:	Δ **CLB Events per million**$_{it}$				
	(1) IV	(2) IV	(3) OLS	(4) OLS	(5) IV
ExpShock$_{it}$	-0.2477***				-1.5725***
	(0.0549)				(0.5536)
Neighboring ExpShock$_{it}$	-0.2999**				
	(0.1286)				
ExpShock$_{i,t+1}$		-0.1051			
		(0.0791)			
ExpShock$_{it}^{Exit}$			-0.5799*		
			(0.3261)		
ExpShock$_{it}^{NonExit}$			-0.0308		
			(0.0954)		
ExpShock$_{it}^{NonSOE}$				-0.1612**	
				(0.0742)	
ExpShock$_{it}^{SOE}$				-0.1495	
				(0.7838)	
(Fiscal Pub. Security$/L)_{i,12}\times$ExpShock$_{it}$					1.1844***
					(0.3334)
Share of SOE Emp$_{i,10}\times$ExpShock$_{it}$					0.2896**
					(0.1105)
Share of Non-Hukou$_{i,10}\times$ExpShock$_{it}$					-0.6645**
					(0.2415)
Share of College$_{i,10}\times$ExpShock$_{it}$					-11.5451***
					(3.7128)
Events per million workers$_{i,t-1}$	-1.0743***	-1.0667***	-1.0792***	-1.0309***	-0.9936***
	(0.1249)	(0.1162)	(0.1100)	(0.1345)	(0.1427)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	37.81	24.38	–	–	8.127
Observations	822	822	822	820	807
R^2	0.6568	0.6486	0.6661	0.6624	0.6404

Notes: The dependent variable is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t. All regressions are weighted by the prefecture's working-age population in 2010. Columns 1, 2 and 5 report IV estimates, while Columns 3 and 4 are OLS regressions. Column 1 controls for a working-age population weighted-average export shock measure in neighboring prefectures; we use an IV that is the corresponding weighted-average Bartik variable across neighboring prefectures. Column 2 examines whether the time t to $t+1$ export shock has explanatory power for the increase in labor strikes between year $t-1$ and t. Column 3 breaks down the export shock into the contribution from firms that exit from exporting versus stayers/new entrants. Column 4 breaks down the contribution of SOEs versus non-SOEs. Column 5 studies heterogeneous effects across prefectures that differ along initial characteristics. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

export for two consecutive years (in years t and $t+1$) – and a remaining component that corresponds to continuing or new exporters. We use the former as a proxy for the exit margin of the export shock, in the absence of direct data on firm or plant closures; we also present OLS estimates, as it is not straightforward to propose two plausible IVs for the separate components of $ExpShock_{it}$. We find in Column 3 that it is indeed the exit margin that drives the overall negative correlation between the export shock and a rise in labor strikes. Column 4 presents an alternative breakdown of $ExpShock_{it}$ into that attributable to state-owned enterprises (SOEs) versus non-SOEs (which includes private domestic and foreign-owned firms). That the non-SOE margin accounts for the export shock effect on labor incidents suggests that SOEs played a role during the export slowdown as a buffer for local employment.

Finally, we investigate in Column 5 how the effects of the export shock varied across prefectures that differ along some key dimensions. We find quite intuitively that the negative effect of an export slowdown on strikes was more muted where the local government: (i) exhibited a greater fiscal capacity to manage unrest (as proxied by the 2012 expenditure per worker on public security uses); and (ii) accounted for a larger share of employment (as proxied by the share of workers employed in government and party agencies, from the 2010 Census). Conversely, the effect of $ExpShock_{it}$ was exacerbated in prefectures with a larger initial share of migrant workers (as measured by the non-hukou population share, from the 2010 Census). This is in line with the view that, with restricted access to social security benefits in the prefecture where they work, migrant workers were less protected from export-induced shocks and hence more prone to strike when economic conditions worsened. Lastly, we find a negative interaction effect between $ExpShock_{it}$ and the population share with at least some college education (from the 2010 Census); this aligns with existing work that has shown that a weak economy is more liable to trigger a rise in protest activity when the local populace features higher levels of educational attainment (Campante and Chor 2012). We naturally caution against a causal interpretation of these results in Column 5, given that we do not propose an instrument for each of these initial prefecture characteristics; it is nevertheless reassuring that the patterns uncovered are consistent with these forces related to the political and economic context in China.

5.2 Further Robustness Checks

In this subsection, we describe an extensive series of checks, including several exercises that draw on recent recommendations pertaining to the use of a Bartik IV strategy. We keep the exposition brisk here in the interest of brevity, with details relegated to Appendix B. While the discussion is written around the effects of the export slowdown on the rise in labor strikes, note that the appendix tables report these checks too for the political response outcome variables (i.e., the textual analysis, fiscal spending, and incumbent turnover measures) that the paper will turn to after this section. (Readers who prefer not to dwell on these checks can proceed directly to that material starting in Section 6.)

Specification Checks: We start by replacing the province-year fixed effects in (2) with region-year fixed effects (Panel A, Table B.1). This retains in the regression sample several economically important prefectures (Beijing, Tianjin, Shanghai, and Chongqing) that would otherwise be dropped, as these are prefectures that make up their entire province. We also run the regressions: (i) without the auxiliary time-t controls, i.e., the change in college-enrolled, mobile-use, and internet-use shares (Panel B); and (ii) without weighting the observations (Panel C).

We consider several alternative specifications to address concerns over the short time dimension and the possibility of Nickell bias in this dynamic panel setting with prefecture fixed effects. In Panel D, we show that the negative effect of the export shock is present even in a pure cross-section of the data – namely, $t = 2015$, the year in which the export slowdown was most severe – while controlling for province fixed effects. In Panel E, we revert to the panel with province-year fixed effects, but drop the prefecture dummies, so that the estimation once again works off cross-sectional variation. In Panel F, we drop $(Events/L)_{i,t-1}$ from the right-hand side, this being the lagged variable that potentially induces the Nickell bias. Reassuringly, our baseline results are not overturned by any of these specification checks. (We moreover show in Appendix B.1 that the plausible direction of the bias would push the $ExpShock_{it}$ coefficient towards zero, leading us to under-state the strength of the negative effect of the export shock.)

We further inspect for potential outlier observations. Figure B.1 in the appendix is a residual scatterplot, based on the estimates from Column 3 of Table 2, which provides visual evidence that no observation is unduly influential for the negative slope coefficient of the export shock variable. In Table B.2, we confirm that no single province is driving the statistical significance of our results, by reporting the range of $ExpShock_{it}$ coefficient estimates when dropping one entire province at a time. (Please see Appendix B.1 for further details).

Other Prefecture-Level Shocks: The interpretation of our results could be undermined if the ROW demand shocks in the Bartik IV were incidentally correlated with demand shocks that originate from within China. If so, our baseline estimates may not be picking up the effects of export demand *per se*. We address this concern by adding a proxy for domestic demand shocks as a control variable. For this proxy, we draw on the China Industry Statistical Yearbooks to compute domestic absorption (i.e., $Absorption_{jt} = Output_{jt} - Export_{jt} + Import_{jt}$) for four-digit Chinese Standard Industrial Classification (CSIC) industries (indexed by j). We then map industry-level changes in absorption ($\Delta Absorption_{jt}$, between years $t-1$ and t) to each prefecture i with the following Bartik-style measure: $AbsorptionShock_{it} = \sum_j \frac{L_{ij,2010}}{\sum_i L_{ij,2010}} \frac{\Delta Absorption_{jt}}{L_{i,2000}}$. Here, $L_{ij,2010}/\sum_i L_{ij,2010}$ is prefecture i's share of industry-j employment (from the 2010 China Annual Survey of Industrial Firms), and $L_{i,2000}$ is the working-age population (from the 2000 Census); see Appendix B.2 for further details and related discussion.[33]

There is an analogous concern that the ROW demand shocks might be correlated with Chinese domestic supply shocks. We address this via a similar approach, by controlling for a

[33]One could in principle construct absorption at the prefecture level directly with the information on firm-level output and location that would be available in the Annual Survey of Industrial Firms. We instead adopted this approach through industry-level absorption, as the Annual Survey is not publicly accessible (to the best of our knowledge) for the years after 2013.

Bartik-style measure of prefecture-level output shocks constructed as above, but with $\Delta Output_{jt}$ in place of $\Delta Absorption_{jt}$. Even with these controls, the estimated effect of the export shock remains robust; this holds regardless of whether we add the domestic demand and output proxies separately (Panels A and B, Table B.3) or jointly (Panel C).[34] We have similarly constructed a prefecture-level import shock measure – by replacing $\Delta Absorption_{jt}$ with $\Delta Import_{jt}$ in the above definition of $AbsorptionShock_{it}$ – to control for changes in imports amidst the broader trade slowdown.[35] Including this measure of import shocks has little bearing on the estimated export shock coefficient (Panel D).

Alternative Bartik IVs: We experiment with alternative constructions of the Bartik IV in Table B.4. In Panel A, we show that our results are similar when we exclude exports by intermediary firms from $ExpShock$ and $ExpShockROW$.[36] This allays the criticism that exports recorded by intermediary firms may not reflect actual shocks to manufacturing production in the local labor market. In Panel B, we incorporate information on export shocks across destinations by constructing the Bartik IV as: $\sum_k \sum_{d \neq CHN} \frac{X_{idk,2010}}{\sum_i X_{idk,2010}} \frac{\Delta X^{ROW}_{dkt}}{L_{i,2010}}$. Here, ΔX^{ROW}_{dkt} denotes the change in exports of product k from the ROW to country d between years $t-1$ and t, while $X_{idk,2010}/\sum_i X_{idk,2010}$ is the share of China's exports of product k to destination d that accrue to prefecture i in the base year (2010). This in principle exploits variation across destinations in product-level demand shocks in the identification strategy. We next follow Redding and Venebles (2004) to back out importer product-specific demand shocks, recovering these off estimates of importer-year fixed effects from gravity equations that have been run separately for each product. We then compute the implied trade shifts that can be attributed to the evolution of these importer-by-product demand forces, and use these to build two Bartik measures: (i) one that is analogous to the baseline IV in (3); and (ii) a version that makes use of the variation across destinations d, that is analogous to the measure in Panel B above. The results when using these respective gravity-based measures as IVs are reported in Panels C and D. We have also worked with an export shock measure that is based on product-level export growth rates, rather than on dollar changes per worker (Panel E). Our main findings remain unaffected under each of these alternatives to our Bartik IV; see Appendix B.3 for additional details.

Validating the Bartik Strategy: We carefully address a number of issues that may affect confidence in the Bartik identification approach. Importantly, like all studies employing Bartik IVs, one has to establish that the results are not simply due to initial specialization in certain

[34]Figure B.2 illustrates that the correlations between $Absorption_{jt}$ and $Output_{jt}$ on the one hand, and the CSIC industry-level export shock on the other hand, are low; the respective slope coefficients are not significantly different from zero. This provides further reassurance that the export slowdown is unlikely to be picking up the roles of domestic demand or supply shocks.

[35]The effect of an increase in imports on labor unrest is in principle ambiguous. On the one hand, imports could replace local production, which could induce more labor-related unrest. On the other hand, imported intermediate inputs may be complementary to domestic labor, and hence reduce strikes instead.

[36]We follow the approach of Ahn et al. (2011) and drop firms with names containing Chinese characters that are the English-equivalent of "importer", "exporter", and/or "trading".

industries that display pre-determined trends, which then are driving the outcomes of interest. For example, labor unrest could be trending up in the textile industry, and hence prefectures specializing in textile products would experience more strikes even in the absence of export shocks. This issue is at the heart of Goldsmith-Pinkham et al. (2018), who emphasize how with Bartik IVs, one can view identification as stemming from the exogeneity of the initial shares. Note that the D_i fixed effects in specification (2) already account for prefecture-specific linear time trends in the outcome variable. To further alleviate concern about unobserved supply shocks with a non-linear pre-trend that are associated with certain products, we show that the results are robust to dropping each individual HS section – and reconstructing the $ExpShock_{it}$ measure and $ExpShockROW_{it}$ IV – one at a time (see Table B.5 and Appendix B.4 for details). In addition, we pick up on the test in Column 2 of Table 5, to show that future export shocks have little explanatory power for contemporaneous outcomes; this holds not just for labor strikes, but also for the set of political response variables we will study (see Table B.6 and Appendix B.5). This indicates that prefecture-specific pre-trends are unlikely to be at the root of our results.

As discussed in Borusyak et al. (2018), the validity of a Bartik IV can be seen instead as stemming from the assumption that shocks – in our case, at the product level – are as good as randomly assigned. This identification assumption may be violated if export demand decreases more in industries that tend to concentrate in prefectures with certain baseline characteristics that themselves have independent effects on local social stability. We therefore follow Borusyak et al. (2018) and test whether the export shocks are balanced across an exposure-weighted average of initial prefecture characteristics, namely: the share of workers with college education, manufacturing employment share, export-to-GDP ratio, non-hukou share of population, log GDP per capita, and log fiscal revenue per capita. Table B.7 reports the results of the balance test, and more details are provided in Appendix B.6. It is reassuring that none of the estimated correlations is statistically significant at conventional levels. Moreover, the p-value for the joint test of significance across all six variables is 0.837.

Alternative Statistical Inference: As a baseline, we have reported standard errors clustered at the province level. In the context of Bartik IVs though, Adão et al. (2019) have pointed out that prefectures located in different provinces could experience correlated shocks if they share a similar initial product-level export mix. We have thus verified that the statistical inference we draw is robust under alternative clustering protocols, including a two-way clustering by province and by a separate partitioning of the prefectures based on an export similarity index (see Table B.8 and Appendix B.7 for details).

5.3 Other Labor Market and Economic Outcomes

Our analysis to this point has focused on labor strikes. That said, if the export slowdown has been affecting local economies in the manner described, we should expect too to observe effects on other outcomes related to employment and output, particularly in the manufacturing sector. Table 6 provides corroborating evidence on this front, using several labor market and economic outcome variables constructed in particular from the China City Statistical Yearbooks. (We adopt the same IV specification as in (2), but replace $\Delta(Event/L)_{it}$ and $(Event/L)_{i,t-1}$ respectively with the change in the outcome measure in question and its lag level.)

Table 6: Effect of Export Shocks on other Economic and Labor Market Outcomes

Dependent variable:	**Δ Economic outcome$_{it}$**					
	Share of Mfg. empl. in population	**Share of Non-Mfg. empl. in population**	**Log Industrial output per capita**	**Log Industrial output per worker**	**Log Night-lights intensity**	**Log Average Wage**
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
ExpShock$_{it}$	0.0046**	-0.0004	0.0106†	0.0188**	0.0058**	0.0043
	(0.0018)	(0.0012)	(0.0062)	(0.0078)	(0.0027)	(0.0036)
Economic outcome$_{i,t-1}$	-1.1614***	-1.4554***	-0.6574***	-1.0209***	-0.9356***	-0.9447***
	(0.0861)	(0.0813)	(0.2330)	(0.1496)	(0.0410)	(0.0734)
Additional time-t controls?	Y	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y	Y
First-stage F-stat	52.07	101.6	77.14	94.86	126.2	155.1
Observations	819	819	822	822	822	809
R^2	0.9677	0.8052	0.7396	0.7768	0.7772	0.6897

Notes: The dependent variables are the prefecture-level economic outcomes in the respective column headings; based on data from the City Statistical Yearbooks, these are computed as the change between year $t-1$ and t. All columns report IV regressions, weighted by the prefecture's working-age population in 2010. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, †p<0.15.

The message that emerges from Table 6 supports the broader narrative that the export shock induced a slowdown in China's manufacturing sector. We find that a decrease in $ExpShock_{it}$ was linked with a fall in the ratio of manufacturing employment to prefecture population (Column 1), with no significant effect on the corresponding ratio for non-manufacturing employment (Column 2). Moreover, gross industrial output in both per capita and per worker terms moved in tandem with manufacturing exports (Columns 3 and 4). We find further corroborating evidence that a weaker export performance was accompanied by a drop in economic activity, as proxied by average night-lights intensity at the prefecture level (Column 5).[37] We obtain an effect on average wages that is of the expected sign – suggesting that a decrease in $ExpShock_{it}$

[37] The implied sizes of these effects are not trivial. In particular, a one-standard deviation more severe contraction in exports ($\approx$ 841 USD per worker) would be associated with a 0.39 percentage point drop in the manufacturing share of prefecture population (Column 1), which can be benchmarked against the in-sample median in this manufacturing employment share of 2.2%. This negative shift in $ExpShock_{it}$ would also be associated with a 0.9% fall in gross industrial output per capita (Column 3), a 1.6% fall in gross industrial output per worker (Column 4), and a 0.5% decrease in night-lights intensity (Column 5).

would lower prefecture wages – although this point estimate is not statistically significant (Column 6). Note though that the average wage measure in the city yearbooks covers only the segment of the workforce with hukou rights; to the extent that migrant workers bore the brunt of a negative export shock, the data would not directly pick up this effect.

6 Political Response to Export Shocks: A Simple Model

We have established that the export slowdown that hit China indeed prompted a rise in incidents of labor unrest. How then did China's political leaders respond? We take on this issue in the second half of this paper, where we study the actions adopted by local leaders who had direct oversight over stability on the ground, and shed light on how these leaders were held to account by decision-makers in the upper levels of government.

To organize our thinking on these fronts, we develop a simple model of career concerns following Persson and Zhuravskaya (2016), that is set up to capture features of China's administrative hierarchy. In the model, a local (prefecture) incumbent can engage in costly measures to bolster social stability when faced with a negative export shock. The local incumbent's performance is in turn evaluated by an upper-level official (in the provincial or central government), who considers whether to retain or remove its local agent. While the model is relatively stylized, it yields predictions on the level of effort expended by the prefecture leader on stability measures that our subsequent empirical analysis can relate to. It moreover sheds light on the nature of the decision rule that would best incentivize the prefecture leader's actions and help in screening out low-ability incumbents.

6.1 Setup

Consider a setting with two time periods. In the first period, the prefecture experiences an external export shock denoted by $x \in [0, 1]$; note that x is increasing in the export performance of the prefecture, so that we associate a *lower* value of x with an export slowdown. The export shock in turn affects local social stability, y, as given by:

$$y = x + (1 - x)s + \varepsilon. \tag{4}$$

The first term, x, reflects the direct (positive) effect of export performance on stability. The second term, $(1 - x)s$, captures the local leader's use of fiscal resources (denoted by s) to counteract the decline in stability that would accompany an export slowdown. We view s as encapsulating public security spending to repress unrest ("sticks"), as well as social spending to soften the economic impact on workers ("carrots"), both of which we observe in the prefecture-level fiscal data. We assume in (4) that the measures s are particularly effective at bolstering social stability when export conditions are weak, or conversely, that these measures are less crucial for stability when exports are healthy. For example, the general public might perceive social spending as less crucial, and might find the use of repression uncalled for, when economic conditions are strong. The final term, $\varepsilon \sim N(0, \sigma^2)$, is an iid stochastic draw, which captures unobserved influences on the realized level of stability.

Our model seeks to capture how the hierarchical administrative system in China serves both to incentivize local leaders' actions and to facilitate the selection of more capable politicians. Towards this latter end, the model incorporates two types of prefecture leaders – G ("good") and B ("bad") – who differ in their competency in delivering local stability. Specifically, local leaders bear a cost $g_\ell(s)$ of adopting stability-enhancing measures, where this cost function differs according to the leaders' type ($\ell = G$ or B). For both types, $g_\ell(s)$ takes on the standard properties of a cost function, with $g_\ell(0) \geq 0$, and $g'_\ell(s), g''_\ell(s) > 0$ for all $s > 0$. We will further assume a functional form below that features: $g'_B(s) > g'_G(s)$ for all $s > 0$, so that the G-type leaders have a lower marginal cost of delivering a given level of stability measures s, this being the key dimension along which the two leader types differ.[38]

The local party secretary (henceforth, he/him) is appointed for one period, but can be retained or replaced for the second. Each period in office affords him rents R. In the first period, after observing the export shock, he decides how much prefecture fiscal resources s to devote to maintaining stability. At the end of the first period, the upper-level government (henceforth, she/her) observes the realized value of stability y, and evaluates the incumbent. We assume that she has complete information about x, so that the export shock itself will not be mis-attributed to the local incumbent's performance. At the same time, she is unable to directly observe the ability type of the incumbent, but knows that there is a share $p \in (0, 1)$ of G-type leaders in the large pool of potential replacement officeholders.

We consider an upper-level government who is only concerned with maximizing expected local stability, i.e., $E(y) = p(1-x)s_G + (1-p)(1-x)s_B + x$, where s_G and s_B denote the levels of s chosen by each respective type of local leader. In Appendix B.8, we show formally that this implies a threshold rule in which she will retain the incumbent if and only if y exceeds $\bar{y}(x)$, while replacing him otherwise from the pool of potential officeholders. Note in particular that the optimal threshold can (and will) depend on the observed export shock, x.

With this in mind, a local leader of type $\ell \in \{G, B\}$ would choose s in order to maximize his expected rents from staying in power, less the costs borne for enacting stability measures:

$$\Pr\left(y > \bar{y}(x)\right) R - g_\ell(s) \;=\; \left(1 - \Phi(\bar{y}(x) - x - (1-x)s)\right) R - g_\ell(s).$$

Here, $\Phi(\cdot)$ is the cdf of the $N(0, \sigma^2)$ normal distribution for ε. The first-order condition with

[38] The model can be extended to allow the incumbent's type to directly raise the stability function. In particular, if the stability delivered by a local leader of type ℓ is: $y = \theta_\ell + x + (1-x)s + \varepsilon$, with $\theta_G \geq \theta_B$, then the model's predictions on stability measures and incumbent turnover carry through.

respect to s for an interior solution is:

$$\phi(\bar{y}(x) - x - (1-x)s)(1-x)R = g'_\ell(s), \tag{5}$$

where $\phi(\cdot)$ is the pdf associated with $\Phi(\cdot)$. For concreteness, we will work with a marginal cost function that implies an equilibrium where the two leader types choose different levels of stability measures, and use this to convey the essential intuition. Specifically, we consider: $g'_\ell(s) = a_\ell + \delta s$, where $\delta > 0$, $a_G = 0$ and $a_B > R/\sqrt{2\pi\sigma^2}$. Since $\phi(\cdot)$ achieves a maximum value of $1/\sqrt{2\pi\sigma^2}$ at $\phi(0)$, this last condition on a_B implies that for a B-type leader, the marginal cost of enacting stability measures exceeds the marginal benefit for all $s > 0$. We thus have $s^*_B = 0$ regardless of $\bar{y}(x)$, as the stability measures are too costly to B-type leaders.

We in turn pin down the optimal level of s for G-type leaders, s^*_G. From the expression above for $E(y)$ and given that $s^*_B = 0$, an upper-level government that seeks to maximize expected stability will clearly seek to elicit the highest possible s_G from G-type incumbents. This is achieved by suitably choosing $\bar{y}(x)$ so that the argument of $\phi(\cdot)$ in (5) is zero, i.e., $\bar{y}(x) = x + (1-x)s_G$. Plugging this into (5), we obtain:

$$s^*_G = \frac{(1-x)R}{\delta\sqrt{2\pi\sigma^2}}. \tag{6}$$

6.2 Model Predictions

We consider the model's implications for two political outcomes which our data will speak to, namely: the resources expended by the prefecture leader on stability measures, and the likelihood of replacement by the upper-level government.

Stability Measures: For G-type leaders, it follows from (6) that in response to negative export shocks: (i) expenditure on stability measures increases ($\frac{ds^*_G}{dx} < 0$). Intuitively, a negative export shock increases the need for and effectiveness of spending to bolster social stability. The increase in expenditure on stability measures is moreover greater for G-type incumbents who: (ii) obtain a higher rent R from being in power ($\frac{d^2 s^*_G}{dx dR} < 0$), and: (iii) incur a lower fiscal cost δ of enacting stability measures ($\frac{d^2 s^*_G}{dx d\delta} > 0$).[39]

Since $s^*_B = 0$, predictions (i)-(iii) also apply to the expected level of stability measures implemented in a prefecture ($ps^*_G + (1-p)s^*_B$), whose leader's type we are not able to directly observe. As we will see in Section 7.2, we will relate the last two predictions to several prefecture and incumbent characteristics that might plausibly capture variation in R and δ.

Turnover: What does the model predict for a local incumbent's likelihood of being replaced? For a G-type leader, it is straightforward to see that $y - \bar{y}^*(x) = \varepsilon$, from which it follows that his probability of turnover is equal to $\Phi(0) = 1/2$ and does not depend on the

[39]Predictions (ii) and (iii) would hold under more general effort cost functions. In particular, it is sufficient (but not necessary) that the marginal cost $g'_G(s)$ be convex at the equilibrium level for s^*_G.

export shock x. This is because the threshold $\bar{y}(x)$ adjusts with the observed export shock: the incumbent is evaluated on a relative benchmark, with the upper-level government accommodating a higher level of instability when prefecture exports are hit by a more severe slowdown. Without this, say if $\bar{y}(x)$ were set at an absolute level instead, the G-type leader would not be properly incentivized to expend resources on stability measures that do not strongly improve his prospects for retention in a bad export slowdown.

The corresponding probability of turnover for a B-type leader is $\Phi(\bar{y}(x) - x)$, since $s_B^* = 0$. It follows then that a B-type incumbent is more likely to be replaced than a G-type for a given observed level of the export shock, as: $\Phi(\bar{y}(x) - x) \;>\; \Phi(\bar{y}(x) - x - (1-x)s_G^*) \;=\; \Phi(0)$. Therefore, the cutoff rule also acts as a screen, in that it results in more capable incumbents being retained with a higher probability.[40]

Last but not least, we examine the implications for the probability of turnover for a given prefecture leader whose type we do not directly observe. Given that the ex-ante share of G-type leaders is p, this probability is: $p\Phi(0) + (1-p)\Phi(\bar{y}(x) - x) \;=\; p\Phi(0) + (1-p)\Phi((1-x)s_G^*)$. Recall from (6) that s_G^* – and hence, $\Phi((1-x)s_G^*)$ – is decreasing in x. Thus, a more severe export slowdown raises the probability of replacement for the local incumbent.

We can gain one further insight on what drives turnover, by introducing a notion of "excess instability" (ES). We define this as: $ES \;\equiv\; \bar{y}(x) - p(x + (1-x)s_G^* + \varepsilon) - (1-p)(x+\varepsilon) \;=\; -\varepsilon + (1-p)(1-x)s_G^*$. In words, "excess instability" captures the extent to which stability in a typical prefecture (whose leader's type we do not observe) falls short of the threshold for leader retention $\bar{y}(x)$. Note that ES is composed of two terms: the first is purely stochastic ($-\varepsilon$) and reflects the role of "luck", while the second term is increasing in the probability that the leader is of type B ($(1-p)(1-x)s_G^*$), and thus reflects how ability (or rather, the lack thereof) contributes to instability.[41] The turnover probability can now be rewritten as:

$$\begin{aligned} p\Phi(0) + (1-p)\Phi((1-x)s_G^*) \;&\approx\; \Phi(0) + (1-p)\phi(0)(1-x)s_G^* \\ &=\; 1/2 + \phi(0)ES + \phi(0)\varepsilon, \end{aligned}$$

where the first step follows from a first-order approximation of $\Phi(\cdot)$ about 0, and the second line follows from the expression for ES. The probability that the local leader will be replaced is thus increasing with "excess instability", namely the extent to which realized stability falls below the threshold $\bar{y}(x)$. This is a prediction we will take to the data with an empirical proxy for "excess strikes" to capture ES, when we study incumbent turnover in Section 8.

[40]Note however that the screen does not achieve a perfect separation in identifying the G-type from the B-type leaders. This is because it is possible for a B-type leader to obtain a favorable stochastic draw ε that raises the realized level of stability above the threshold $\bar{y}(x)$.

[41]The "luck" component is related to the literature that has investigated whether incumbents are punished for outcomes beyond their control in democracies; see Fowler and Hall (2018), and Achen and Bartels (2018).

7 Political Response: Preserving Social Stability

We now turn to the empirical investigation on the political reaction to the export slowdown and the rise in labor unrest. We document that these developments triggered a more acute concern over social stability, both from the public at large and from local officeholders. The latter was reflected in an increased emphasis on law and order in prefecture annual work reports. This was accompanied by actual increases in prefecture spending on stability measures, in line with the model's predictions.

7.1 Attention to Preserving Stability

We adopt a novel approach to measure the degree of attention paid to the issue of public security, that is based on the use of key political phrases – in particular, "weiwen" (in Chinese, "维稳") – in the public domain. The term "weiwen" is a contraction of "维护稳定", which literally translates as "maintaining stability"; it was reportedly first used in the official People's Daily newspaper in 2002, in an article that was accompanied by a photograph of armed police. Since then, the term "weiwen" has been adopted as a watchword by the political authorities, and is widely used to refer to actions to maintain law and order in the interest of preserving domestic stability (*New York Times*, 2012).

We will make use of the above observation in two ways, to construct measures that will be amenable to empirical analysis. First, we investigate the response of internet search volumes for the term "weiwen" at the prefecture level in the aftermath of a local strike event, as an indicator of the attention paid to domestic security issues by the general public. This will help validate the premise that the public associates the occurrence of labor strikes with concerns about social stability and law and order. Second, we use this term as the basis for a textual analysis of prefecture annual work reports, to measure the degree to which preserving social stability features as a political priority of the local government; in particular, we explore whether there is a systematic shift in "weiwen" emphasis following a negative export shock.

7.1.1 Public Concern: Baidu Search Index

We follow a growing body of empirical work in the economics literature that has used data on the intensity of internet searches, based on such metrics as Google Trends, to gauge the pattern of internet users' interests and attitudes on socioeconomic or political issues (Madestam et al. 2013; Stephens-Davidowitz 2014; Kearney and Levine 2015). For our purposes, Google Trends is unlikely to reflect the true search volume among domestic Chinese internet users, as access to Google has been severely curtailed in mainland China since 2010. We thus turn instead to the counterpart of Google Trends on the largest search engine in China, Baidu. Note that Baidu's market share is estimated to be between 60-70% of internet users in China.[42]

The Baidu Index allows users to retrieve information at a weekly frequency on the volume of search queries for specific keywords, and can moreover distinguish searches by the prefectures from which they originate. We therefore scrape the Baidu Index for the keyword "weiwen", both over time and by prefecture. Although Baidu does not publicly disclose the exact formula for its index, prior researchers have verified that the Baidu Index is likely to be linearly correlated with the volume of public searches recorded for a given keyword (Qin and Zhu 2017).[43]

We demonstrate that public attention to "weiwen" is indeed related to the occurrence of strikes, by exploiting the rich weekly dimension of the CLB strike data together with the above Baidu "weiwen" index. The structure of the merged data lend themselves to an event-study analysis, which we implement in the following regression:

$$\Delta \ln(Baidu)_{i,w} = \sum_{l=-2}^{6} \lambda_l \Delta(Events/L)_{i,w-l} + \lambda \ln(Baidu)_{i,w-1} + D_{p,w} + D_i + \varepsilon_{i,w}. \qquad (7)$$

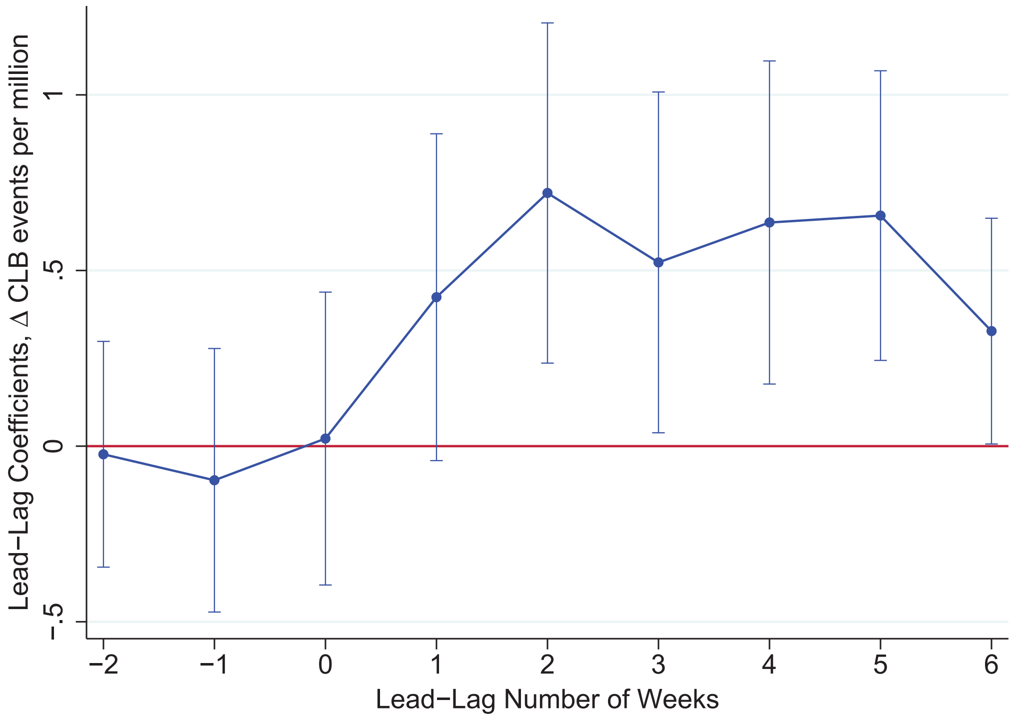
Here, $\Delta \ln(Baidu)_{i,w}$ is the change in the log Baidu "weiwen" index in prefecture i and week w (i.e., relative to week $w-1$). We regress this against a set of leads and lags of the change in CLB events per worker observed in that prefecture (where $\Delta(Events/L)_{i,w-l} = (Events/L)_{i,w-l} - (Events/L)_{i,w-l-1}$), as well as against the lag level of the search index itself in week $w-1$. The $D_{p,w}$ and D_i denote province-by-week and prefecture dummies respectively. The flexible lead-and-lag structure allows us to track the dynamic effects of labor strikes on public attention to "weiwen"-related issues. We estimate the above for a panel of weekly observations spanning 2012-2015, although the results are very similar if we were to expand the sample to 2011-2016 (available on request).

Figure 4 illustrates the estimates of the λ_l's from (7), together with the 90% confidence intervals; these are based on standard errors clustered by prefecture, to account for potential serial correlation in how the intensity of strikes might evolve in a given location. We find that lead values of changes in strike intensity ($l = -2, -1$) have no statistically significant effect on the search volume for the term "weiwen". Of note, this search volume picks up in response to past increases in labor strikes, with the reaction in the Baidu index then persisting for up to six weeks. (The full set of estimates is reported in Table B.9 in the appendix. There, we show that the above pattern in the λ_l coefficients is robust if one were to drop the prefecture fixed effects, or if one were to estimate the regressions with working-age population weights.)

[42]See: https://www.wsj.com/articles/bing-baidu-and-a-big-mess-for-chinese-search-engines-11548328142

[43]By contrast, Google Trends reports a "relative search index", which is the ratio of the search volume for a given term to the total number of searches conducted in a particular time/location. The publicly-available information from Google Trends thus only has an ordinal interpretation (Kearney and Levine 2015). On the other hand, the Baidu Index appears to be a cardinal measure, which facilitates comparisons across time and location. The Baidu Index comes in the form of a graphed time series, so an algorithm was written to read the value of the index off the pixels in the graphics file for each prefecture.

Figure 4: Temporal Correlation between Baidu "Weiwen" Search Index and CLB Events



The above finding provides evidence of a significant response in terms of a rise in attention paid by netizens to the issue of public security following increases in local incidents of labor strikes. This could reflect for example a rise in concern about the law and order situation in one's prefecture, or an increase in internet searches related to media coverage of a new "weiwen" policy to bolster stability. At a more basic level, this exercise also serves to validate the use of "weiwen" as a keyword, in that the frequency of its use can shed light on the intensity of responses to local unrest events.

7.1.2 Local Government Concern: Annual Work Reports

We next extract information on the political emphasis on maintaining social stability from an official document of the local government, namely the prefecture annual work report. Within China's political system, this report is delivered as a speech at the prefecture-level People's Congress meeting usually held in January each year. The reports are relatively uniform in their format, which is helpful for our implementation of a textual analysis. Each report comes in two sections. The first section is a summary of socioeconomic conditions from the preceding year, often rendered as a list of the local government's accomplishments. On occasion, this material mentions instances of high-profile strikes or unrest events that drew the government's attention. The second section then lays out development policies for the year ahead. Apart from describing economic plans, this includes measures intended to check and mitigate social unrest (i.e., "weiwen" actions) in prefectures where this may be a relevant issue.

We use two different approaches to construct measures of a work report's emphasis on preserving social stability. Our more basic approach involves a simple count of "weiwen"-related keywords. For this, we scan each prefecture's work report for each year between 2013-2016, and count the number of occurrences of eleven keywords. This list of keywords naturally contains "weiwen" ("维稳"), its unabbreviated form ("维护稳定"), and several variants (e.g., "和谐稳定" or "harmony and stability", "安全稳定" or "safety and stability"); it also includes several synonyms for public security (e.g., "公共安全"). (The full list of keywords and their translation is in Table A.1.) The keyword count is then normalized by the total count of Chinese characters in the associated work report.

We also implement a more sophisticated machine-learning approach to compute "weiwen" scores for each report. For this, we first randomly selected 20 reports from a pre-sample year (2011), to mark out all sentences as either being about "weiwen" or "not-weiwen". These labelled passages were used, together with a paragraph from a national-level State Council document dated April 2015 on the topic of domestic security measures, as the training sample for the algorithms.[44] We then tokenize the text of each annual work report using an online Chinese word library, before applying two machine-learning algorithms: (i) the Multinomial Naive Bayes (MNB), and (ii) the Support Vector Machine (SVM). The MNB model generates a posterior probability that a paragraph is on the topic of "weiwen", using an underlying multinomial distribution model of token frequencies. The SVM on the other hand is a binary classifier, that generates a 0-1 prediction for whether a paragraph is about "weiwen", after partitioning the observations in a high-dimensional metric space. (See Appendix A.5 for more technical details.) We compute a report-level score, by taking the character-length weighted-average of the paragraph scores. We view these "weiwen" scores as capturing the degree to which maintaining social stability was an announced policy priority for the local government in the prefecture and year in question.[45] As a placebo test, we have checked the predictions that the trained algorithms deliver on paragraphs that are related to tackling economic volatility (such as in stock or real estate prices), given that the Chinese phrase ("稳定") is also used in references to economic stabilization policies. Both MNB and SVM models returned "weiwen" scores close to zero for such passages, verifying the algorithms' ability to discriminate between content related to economic versus political stability.

With these textual analysis measures, we estimate the following regression model to examine

[44]The State Council document was entitled "Opinions on Strengthening Society's Public Security Prevention and Control System", and provides a set of recommendations on "weiwen" measures. See: http://www.gov.cn/xinwen/2015-04/13/content_2846013.htm

[45]Our approach thus makes use of "supervised" machine-learning algorithms, in that the algorithm is trained to recognize "weiwen" versus "non-weiwen" passages instead of being allowed free rein to identify textual associations. This is similar to the approach in Gentzkow and Shapiro (2010), who use a keyword approach to identify the political slant of U.S. newspapers. For other applications of machine-learning methods to classify free text in empirical research in economics, see the survey article of Mullainathan and Spiess (2017).

whether export shocks induced a political response in terms of "weiwen" emphasis:

$$\Delta y_{i,t+1} = \gamma_1 ExpShock_{it} + \gamma_2 y_{it} + \gamma_X X_{it} + D_{pt} + D_i + \varepsilon_{it}. \quad (8)$$

This specification is similar to that in (2), with a textual analysis score (denoted by y) now being used in place of the CLB events variable. Note that (8) seeks to explain changes in the political response variable y between years t and $t+1$, as a function of the export shock in the preceding year. We lead the response variable on the left-hand side by one period for two reasons. First, this accommodates a lag in how quickly political actions would respond to an adverse economic shock whose severity may not be fully anticipated. Second, the prefecture work reports are delivered at the start of each calendar year, with the content and wording influenced by socioeconomic conditions in the preceding year. We therefore relate the change in political emphasis on stability that is quantified from work reports in year $t+1$ to export shocks in year t, where $t \in \{2013, 2014, 2015\}$; in other words, we associate these export shock observations with the political responses $\Delta y_{i,t+1}$ between 2013-2014, 2014-2015, and 2015-2016 respectively. As before, we instrument for the export shock with the Bartik IV from (3), while controlling for province-year and prefecture fixed effects; the regressions are weighted by the prefecture working-age population in 2010, with standard errors clustered by province. In particular, the province-year fixed effects are important as they help to control for variation over time in the overall intensity of the use of the term "weiwen", which could be due to broader political directives at the national or provincial level.[46]

Table 7 presents the results from this analysis of the prefecture annual work reports. For each measure, the odd-numbered columns report a basic specification without prefecture time-varying controls (X_{it}), while the even-numbered columns include the prefecture-level changes in the college-enrolled, mobile-use and internet-use shares, as seen earlier in Column 3 of Table 2. We obtain a consistent pattern regardless of the textual-analysis dependent variable or auxiliary controls adopted, namely that a negative export shock raises the emphasis placed by local officeholders on maintaining social stability, to the extent that these are reflected in the annual work reports they deliver. (We have also repeated the full set of checks described earlier in Section 5.2 to assess the robustness of these effects of the export shock on "weiwen" emphasis; these are reported using the MNB "weiwen" measure in Column 2 of the corresponding Appendix B tables.) Looking across Columns 3-6 of Table 7, the implied effect of a one standard deviation increase in the severity of the export shock ($\approx$ 841 USD per worker) would be to raise the "weiwen" score by between 13-16%. The above findings therefore underscore the political importance that the prefecture governments attach to upholding public security and stability in response to the export slowdown.

[46]For example, the summary statistics in Table 1 point to a decrease on average in "weiwen" scores from 2015-2016, but Table 7 confirms that in the residual variation after controlling for this year-specific shift, we are able to identify a relationship running from a negative export shock to an increased emphasis on "weiwen".

Table 7: Export Shocks and "Weiwen" Emphasis

Dependent variable:	Δ **Textual "weiwen" score**$_{i,t+1}$					
	Share of keywords	**Share of keywords**	**Log MNB**	**Log MNB**	**Log SVM**	**Log SVM**
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
ExpShock$_{it}$	-0.0023*	-0.0021†	-0.1600**	-0.1904**	-0.1535***	-0.1714***
	(0.0012)	(0.0012)	(0.0772)	(0.0725)	(0.0545)	(0.0577)
Textual "weiwen" score$_{it}$	-1.2997***	-1.3176***	-29.6643***	-31.3318***	-41.1034***	-41.7952***
	(0.0421)	(0.0360)	(3.6840)	(4.1088)	(3.0013)	(3.0813)
Additional time-t controls?	N	Y	N	Y	N	Y
Prefecture dummies?	Y	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y	Y
First-stage F-stat	64.41	103.2	52.63	77.54	61.85	97.54
Observations	923	802	923	802	923	802
R^2	0.7706	0.7671	0.5022	0.5146	0.5938	0.6022

Notes: The dependent variable is the change in textual "weiwen" score in prefecture i between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010. Columns 1 and 2 regress the change in "weiwen" keyword share against the initial level of the keyword share. Columns 3 and 4 regress the change in log Multinomial Naive Bayes (MNB) score against the initial level of the MNB score. Columns 5 and 6 regress the change in log Support Vector Machine (SVM) score against the initial level of the SVM score. The additional time-t controls in even-numbered columns are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

7.2 Fiscal Expenditure

The analysis from the previous subsection is useful for capturing the announced intentions of the local government, but does this translate into the allocation of tangible resources towards maintaining social stability, as suggested by our framework from Section 6? We turn to this issue now, to study how the export slowdown affected the use of prefecture fiscal resources.

Toward this end, we collected data on realized fiscal expenditures and their detailed structure by spending categories. There is no one-stop repository of local-level fiscal data for China (to the best of our knowledge), and so these data were gathered from several sources. The majority of the data are from the Fiscal Statistical Yearbooks published by the provincial Bureau of Finance, and the Statistical Yearbooks published by the provincial Bureau of Statistics, from provinces across China. These are supplemented with information from prefecture statistical yearbooks, as well as balance sheets from prefecture government websites. In all, we were able to gather data for up to 95% of the prefecture-year observations in our sample. Note that subnational governments in China are responsible for 85% of government spending (Wingender 2018), and so are a meaningful locus of decision-making over the use of fiscal resources.

We focus our attention on two broad categories of spending that capture measures to bolster local stability. The first is spending on public security uses. This includes all expenses by the People's Armed Police, public security organs, court system, judicial system, and prosecutorial system. On the other end of the spectrum, we consider forms of expenditures – which we place under the label of "social spending" – that could in principle assuage citizens' discontent. These include: public services, education, social security, medical services, and public housing. To give a sense of how these spending items compare against each other, the share of prefecture fiscal expenditure on public security averaged 5.1% during the years 2013-2016. By contrast, the average share on social spending was 54.2%, with the largest components of this being education (17.8%), social security (12.6%), and public services (10.1%).[47]

We follow the IV specification in (8) to assess the impact of export performance on patterns of fiscal spending at the prefecture level. Specifically, we regress changes in log fiscal spending in year $t + 1$ on export shocks in the prior period (year t); in other words, we use the log of each expenditure item in turn as the variable y in equation (8). We report the estimates from these in Panel A of Table 8.

In Column 1, we demonstrate that total spending on stability measures – the sum of public security and social spending – indeed rises in response to a negative export shock. This increase is statistically significant for each component, when we consider public security (Column 1a) and social spending (Column 1b) separately. In terms of magnitude, the estimated coefficients imply that a one standard deviation worse export shock (≈841 USD per worker) would prompt a 1.8% increase in public security spending, which is slightly larger than the corresponding 1.3% increase in social spending.[48] In Table B.11 in the appendix, we break down social spending further into several sub-components; the findings here show that an export slowdown prompts a broad increase across most categories of social spending, including that on public services, medical services and public housing.[49] Coming back to Table 8, we find in Column 2 that the response of other forms of spending (i.e., all categories not related to public security or social spending) is less pronounced and not statistically significant, even while Column 3 confirms that a bad export shock would induce a significant rise in total prefecture fiscal expenditures.

On the whole, fiscal policy at the local level is thus counter-cyclical with respect to the prefecture's export performance, and this is mostly driven by the increase in spending on budget items that can be viewed as stability-enhancing measures. In relation to this, Column 4 indicates that locally-raised fiscal revenues (i.e., excluding transfers from the central government) also increase during an export slowdown, suggesting that the local authorities in China possess the fiscal tools and capacity to increase revenues, in support of a rise in discretionary spending.

[47]Public security and social spending thus constituted around 60% of the total expenditures for the average prefecture. The main remaining expenditure items are arguably less relevant for mitigating labor unrest, namely: agriculture, forestry, and water conservancy; transport; and urban and rural community affairs.

[48]In the tables in Appendix B, specifically in Columns 3 and 4, we document the robustness of these findings – for log changes in spending on public security and log changes in social spending – to the various concerns discussed in Section 5.2. Separately, Table B.10 presents the results when we work instead with the spending items expressed as shares of total expenditure; we arrive at a similar set of conclusions.

[49]We do not undertake a similar exploration with the components of spending on public security, as the underlying raw data do not provide a breakdown across comparable sub-categories for a large enough number of prefectures.

While a full exploration of the sources of these revenues is outside the scope of our paper, there is evidence in the existing literature pointing to the local governments' ability to clamp down on tax evasion or undertake land sales for this purpose.[50]

Table 8: Export Shocks and Prefecture Fiscal Measures

Dependent variable:	Δ **Log Fiscal measure**$_{i,t+1}$					
Fiscal measure:	**Stability Measures**	**Public Security**	**Social Spending**	**Other Spending**	**Total Expenditure**	**Total Revenue**
	(1)	(1a)	(1b)	(2)	(3)	(4)
	IV	IV	IV	IV	IV	IV
	Panel A: Average Effects					
ExpShock$_{it}$	-0.0163***	-0.0214***	-0.0160**	-0.0103	-0.0114***	-0.0200***
	(0.0054)	(0.0069)	(0.0059)	(0.0063)	(0.0040)	(0.0035)
Log Fiscal Measure$_{it}$	-0.9701***	-0.9356***	-0.9590***	-0.7744***	-0.7446***	-0.6328***
	(0.0493)	(0.0551)	(0.0492)	(0.0516)	(0.0727)	(0.0777)
First-stage F-stat	189.1	117.9	183.7	133.1	98.01	92.74
Observations	755	812	760	755	817	822
R^2	0.7801	0.7747	0.7805	0.8103	0.8050	0.8232
	Panel B: Heterogeneous Effects					
ExpShock$_{it}$	0.0633***	-0.0518**	0.0815***	0.0840**	0.0608**	-0.0044
	(0.0143)	(0.0231)	(0.0166)	(0.0348)	(0.0232)	(0.0176)
Δ(Events/L)$_{it}\times$ExpShock$_{it}$	-0.0149***	-0.0100***	-0.0160***	-0.0186***	-0.0171***	-0.0136***
	(0.0023)	(0.0020)	(0.0026)	(0.0062)	(0.0045)	(0.0041)
(FiscalRev/L)$_{i,2012}\times$ExpShock$_{it}$	-0.0335***	0.0337**	-0.0440***	-0.0392**	-0.0262**	0.0068
	(0.0082)	(0.0134)	(0.0093)	(0.0182)	(0.0114)	(0.0135)
(49$\leq$Age$\leq$53)$_{it}\times$ExpShock$_{it}$	-0.0228***	-0.0231*	-0.0229***	-0.0164	-0.0157	-0.0218***
	(0.0055)	(0.0126)	(0.0055)	(0.0178)	(0.0109)	(0.0078)
Δ(Events/L)$_{it}$	0.0009	-0.0001	0.0013	0.0005	0.0010	-0.0049
	(0.0021)	(0.0039)	(0.0021)	(0.0055)	(0.0031)	(0.0034)
(49$\leq$Age$\leq$53)$_{it}$	-0.0132**	-0.0106	-0.0128*	-0.0167	-0.0135*	-0.0222**
	(0.0062)	(0.0102)	(0.0069)	(0.0131)	(0.0071)	(0.0091)
Log Fiscal Measure$_{it}$	-0.9663***	-0.9665***	-0.9554***	-0.7954***	-0.7823***	-0.6454***
	(0.0435)	(0.0565)	(0.0446)	(0.0594)	(0.0667)	(0.0722)
First-stage F-stat	17.03	18.36	18.08	12.93	14.01	20.32
Observations	755	812	760	755	817	822
R^2	0.7841	0.7647	0.7832	0.8002	0.7944	0.8272
Additional time-t controls?	Y	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is the change in log fiscal measure under the respective column headings in prefecture i between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010. Panel A reports the average effects of the export shock on the respective fiscal measures. Panel B explores heterogeneous effects: The Δ(Events/L)$_{it}$ variable is the change in CLB-recorded events per million between year $t-1$ and t. (FiscalRev/L)$_{i,2012}$ is the local fiscal revenue per worker in 2012. (49$\leq$Age$\leq$53)$_{it}$ is a dummy variable for whether the prefecture party secretary is between ages 49 and 53 (inclusive) in year t. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Panel B of Table 8 delves into whether the effects of export shocks on fiscal spending patterns might differ systematically across prefectures. We focus our discussion here on the

[50] See, for example, Chen (2017). This is in contrast to the situation in the United States highlighted by Feler and Senses (2017), where negative trade shocks tightened budgets and hurt local public goods provision.

findings in Columns 1a and 1b for public security and social spending respectively. We consider first an interaction between the export shock and the increase in CLB-recorded strikes per worker observed in the previous year, $\Delta(Events/L)_{it}$, in order to explore whether the fiscal spending effects were prompted (at least in part) by concerns over labor disputes. The estimated interaction coefficients are negative and significant in both Columns 1a and 1b, indicating that fiscal responses to a negative export shock are stronger for both "stick" and "carrot" measures when there is a more severe increase in labor strikes, and hence (potentially) a greater threat to social stability.

Motivated by predictions (ii) and (iii) from our framework in Section 6, we also consider whether the impact of the export shock might vary with the career prospects of the local incumbent and with local fiscal capacity. On the former, we explore an interaction term involving a dummy variable for whether the prefecture party secretary is between ages 49-53 in year t. As established in Appendix A.6, the likelihood of promotion for a local party leader peaks between these ages, and we thus take this dummy as a proxy for officeholders who have higher expected rents (R) from holding political office. We find that its interaction coefficient with the export shock is negative and significant for both public security and social spending. Politicians with greater promotion prospects are thus more likely to increase spending on measures to bolster stability following a bad export shock, in line with the logic of our model.

On initial fiscal capacity, we use as a proxy the level of fiscal revenue per worker in 2012. We find that this interaction effect with the export shock variable is negative and significant for total spending on stability measures (Column 1). Prefecture governments who face fewer fiscal constraints thus raise their spending on stability measures more strongly, consistent with the implications associated with a lower δ in our model. Interestingly, local governments with deeper fiscal pockets are less inclined to raise public security spending following a negative export shock (Column 1a), and more inclined instead to raise social spending (Column 1b). While our stylized model does not capture this heterogeneous response across different forms of spending, we hypothesize that this could be due to social spending requiring a more sustained, intensive use of fiscal resources than a short-term ramping up of public security.

8 Political Response: Incumbent Turnover

In this last empirical section, we present evidence on the response of the upper-level government, by examining how the export slowdown affected decisions over the retention or replacement of local party leaders. In particular, the model in Section 6 implies that prefecture leaders would be assessed on the basis of their performance in maintaining social stability after taking into account the severity of the export shock. We thus explore the extent to which the observed career paths of these party officials is in line with the model's predictions.

8.1 Data and Specification

We collected information on the biographic characteristics and career histories of local party secretaries from their curricula vitae. These were compiled from the database of leaders maintained by People.cn, an official website affiliated with the Chinese government.[51] The data cover 544 individuals who held the position of prefecture party secretary over the period 2013-2016, and allows us to track the month and year in which each individual took and/or left office. We focus on party secretaries, as this is the top executive position at the prefecture level, with ultimate authority and substantial discretion over local fiscal and regulatory policies (Persson and Zhuravskaya 2016). The party secretary is also in charge of personnel and other political duties such as maintaining social stability, while the mayor (the second in rank) is in charge of the daily operations of the government (Yao and Zhang 2015). To the extent that the party secretary bears greater responsibility for local stability, his/her career trajectory would be more susceptible to any social unrest associated with negative economic shocks.

We define $Turnover_{it}$ to be an indicator variable equal to 1 when there is a change in party secretary in prefecture i in a given calendar year t. Over 2014-2016, the average annual turnover rate for prefecture party secretaries was 29.6% (see Table 1). We further classified the nature of each instance of turnover as: a promotion, a lateral movement, or due to other causes (e.g., corruption, retirement, movement to an honorary position). We are helped here by the fact that China's political system has an administrative hierarchy of positions. This starts at the top with national-level appointments, followed in descending order by positions at the sub-national, province, sub-province, prefecture, and sub-prefecture levels. In our coding, we define a promotion as a move by a prefecture party secretary to a post that is at the sub-provincial level or above, while a lateral movement is a transfer to a different prefecture-level position; see though Appendix A.6 where we detail a number of exceptions to this coding rule.[52] Based on this criterion, 25% of the instances of turnover during 2014-2016 are promotions, and 55.1% are lateral movements. The remaining cases are a combination of retirements or terminations of political career (e.g., due to corruption). There were in fact no cases where a prefecture party secretary was demoted to a position at the sub-prefecture level or below.

The fact that there are no observed demotions in rank suggests that punishment for weak

[51]See: http://ldzl.people.com.cn/dfzlk/front/firstPage.htm. We supplement this with information from Wikipedia where necessary.

[52]First, several prefectures are officially designated as provincial-level or sub-provincial-level administrative units (e.g., Beijing); the party secretary positions in these locations are thus of higher rank, and we classify movements into and out of these positions on the basis of this higher rank. Second, we do not categorize appointments to several honorary positions as promotions (e.g., chairman of the province-level People's Congress); even though these are nominally of sub-province rank, the positions are viewed as "consolation prizes" or retirement posts (Li and Zhou 2005, Yao and Zhang 2015). Third, some prefecture party secretaries simultaneously hold positions that rank at the sub-provincial level (e.g., member of the provincial standing committee); for such cases, we consider a movement to another position at the sub-provincial level (e.g., a vice-provincial governor) as a lateral movement.

performance takes a different form within China's political system. We therefore examine more closely the nature of the lateral movements. Existing guidelines indicate that prefectural officials should have served at least three years in a position, before being eligible for promotion to the next level in the political hierarchy; this is announced for example in the *Regulations for the Selection and Appointment of Party Cadres*, by the Organizational Department of the Chinese Communist Party.[53] Based on this, we label lateral moves that occurred prior to the three-year mark in the prefecture party secretary's tenure as cases of "early" lateral movement. In our sample period, 31.1% of the lateral movements are classified as "early". In Appendix A.6, we provide empirical evidence confirming that among officeholders who had been moved laterally, those who were moved early had a lower likelihood of future promotion compared to those who had served in their prior positions for the requisite three years.[54] We thus associate such "early" lateral movements with a *de facto* demotion, since it tends to slow down an official's career trajectory.

Using this data on incumbent turnover, we estimate regressions of the following form, following closely the earlier specification in (8):

$$Turnover_{i,t+1} = \theta_1 ExpShock_{it} + \theta_2 Turnover_{it} + \theta_X X_{it} + D_{pt} + D_i + \varepsilon_{it}. \tag{9}$$

In words, this investigates how the likelihood of replacement of the party secretary in year $t+1$ might depend on the export shock experienced in the prefecture in year t. As before, we instrument $ExpShock_{it}$ with the Bartik IV from (3), while controlling throughout for province-year and prefecture fixed effects. In addition to the prefecture time-varying controls from (8), we include in X_{it} a set of incumbent characteristics extracted from their curricula vitae, namely: gender, age, education (whether he/she possesses a Masters degree or higher), and tenure as party secretary (in years). We also construct a dummy variable for whether the incumbent's current appointment is in his/her province of birth, and use this as a proxy for the strength of his/her ties with local political networks.

We take this analysis of the determinants of political turnover one step further, motivated by insights from our Section 6 model. Recall there that the upper-level government is cognizant that an export slowdown would induce a rise in worker unrest. In order to properly incentivize local leaders to bolster stability even when there has been a bad export shock, the upper-level government's decision over whether to replace the incumbent would have to depend not on the absolute level of instability *per se*, but on the extent to which the instability can be seen as excessive. We seek to capture this notion of "excess instability" with a measure of "excess strikes", which we construct in an intuitive way from the data. Specifically, we take the IV regression residuals from Column 3 of Table 2, this being variation in the increase in strikes

[53] See: http://www.people.com.cn/GB/shizheng/16/20020723/782504.html.

[54] This analysis is based on a sample of prefecture party secretaries who experienced a lateral movement during 2007-2012, and considers their observed career histories up until 2016 where our data end.

per worker, $\Delta(Events/L)_{it}$, that is not explained by the observed export shock. We then order these regression residuals into terciles, and augment the specification in (8) by adding dummies for the medium and highest "Excess Strike" terciles as explanatory variables. This allows us to explore whether the extent of excess labor unrest measured as such – which through the lens of our model could reflect either weak incumbent ability or stochastic forces outside his/her control ("luck") – can explain turnover outcomes.

8.2 Results

Table 9 reports our key results from estimating (9). Column 1 demonstrates that the incumbent party secretary was indeed more likely to be replaced following a downturn in prefecture exports. In particular, a one standard deviation more negative export shock would raise the likelihood of turnover by $0.841 \times 0.0742 \approx 6.2$ percentage points, a fairly sizeable effect when compared against the average turnover rate of 29.6% in our sample period. (As reported in Column 5 of the Appendix B tables, this link from the export shock to incumbent turnover is robust under the alternative specifications and checks discussed in Section 5.2.)

After including the "Excess Strike" variables in Column 2, we obtain positive and significant coefficients on both the medium and high tercile dummies. This suggests that party secretaries were held to account for the labor strike situation in their prefectures: a large spike in strikes over and above what can be explained by the observed export shock is associated with a higher likelihood of replacement. The estimated effects are large, with the coefficients pointing to a 10.9 and 14.3 percentage point increase in turnover probability in the medium and high "Excess Strike" terciles respectively.[55]

We separately examine the two main categories of incumbent turnover in the remainder of Table 9. For this purpose, we define $Turnover_{i,t+1}$ and its lag in (9) as indicator variables for lateral movement (Columns 3-4) and promotion (Columns 5-6) respectively. We find here that it is movements of a lateral nature that rise in response to a bad export shock (Column 3), and particularly if this is accompanied by an excessive level of strike activity (Column 4). On the other hand, our baseline turnover results are not being driven by promotions, as both the export shock and "Excess Strike" variables exhibit small and insignificant effects (Columns 5-6). For prefecture party secretaries, the ability to deliver a low level of "Excess Strikes" thus appears to be necessary but not sufficient to raise one's chances of promotion. Interestingly, there is one incumbent characteristic – being born in the province – that is linked with both a higher promotion probability and a lower likelihood of lateral movement, suggesting that

[55]We obtain similar coefficients on the "Excess Strike" terciles, in terms of both sign and statistical significance, if we were to take out the export shock variable from the right-hand side and re-run (9) as an OLS regression. We have also obtained comparable results when working with alternative ways of generating the regression residuals that define the "Excess Strike" terciles, namely: (i) including the incumbent characteristics from Table 9 as additional controls in the Table 2, Column 3 specification; and (ii) using the Table 2, Column 4 reduced-form OLS specification instead.

Table 9: Export Shocks and Party Secretary Turnover

Dependent variable:	Party Secretary Turnover$_{i,t+1}$					
	Turnover		**Lateral**		**Promotion**	
	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
ExpShock$_{it}$	-0.0742***	-0.0644***	-0.0579*	-0.0500	-0.0025	-0.0021
	(0.0192)	(0.0196)	(0.0314)	(0.0307)	(0.0119)	(0.0113)
ExcessStrike$^M_{it}$: Medium Tercile		0.1088**		0.0795**		0.0063
		(0.0508)		(0.0345)		(0.0241)
ExcessStrike$^H_{it}$: High Tercile		0.1428**		0.1206**		-0.0008
		(0.0533)		(0.0462)		(0.0176)
Turnover Variable$_{it}$	-0.6844***	-0.6888***	-0.4607***	-0.4722***	-0.2790***	-0.2794***
	(0.0515)	(0.0548)	(0.0584)	(0.0643)	(0.0636)	(0.0622)
Incumbent Characteristics:						
Tenure$_{it}$	0.1866***	0.1923***	0.0620***	0.0668***	0.0142**	0.0142**
	(0.0154)	(0.0167)	(0.0128)	(0.0135)	(0.0052)	(0.0052)
(Age≤48)$_{it}$	0.0204	0.0478	0.0627	0.0856	0.0095	0.0101
	(0.1369)	(0.1444)	(0.1184)	(0.1222)	(0.0681)	(0.0677)
(49≤Age≤53)$_{it}$	-0.0841	-0.0839	-0.0922	-0.0924	0.0430*	0.0429*
	(0.0551)	(0.0574)	(0.0637)	(0.0628)	(0.0249)	(0.0249)
Born in the same province$_{it}$	0.0524	0.0604	-0.1168**	-0.1113**	0.0477**	0.0478**
	(0.0804)	(0.0787)	(0.0522)	(0.0466)	(0.0221)	(0.0223)
Master degree or above$_{it}$	-0.1448	-0.1253	-0.2259***	-0.2105***	-0.0302	-0.0307
	(0.0865)	(0.0862)	(0.0586)	(0.0592)	(0.0337)	(0.0333)
Female$_{it}$	0.1347	0.1222	0.1519	0.1420	-0.1369*	-0.1374*
	(0.1895)	(0.1821)	(0.1401)	(0.1304)	(0.0739)	(0.0737)
Additional time-t controls?	Y	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y	Y
First-stage F-stat	94.38	73.97	83.64	65.60	84.33	67.98
Observations	822	822	822	822	822	822
R^2	0.5472	0.5642	0.5093	0.5247	0.4899	0.4899

Notes: The dependent variable in each column is a dummy for whether there was a change in prefecture party secretary in year $t+1$ (i.e., one year after the export shock. This is coded up for all forms of turnover (Columns 1-2), lateral movements (Columns 3-4), and promotions (Columns 5-6), respectively; Turnover Variable$_{it}$ is the one-year lag of the dependent variable in each column. All columns report IV regressions, weighted by the prefecture's working-age population in 2010. The ExcessStrike$^M_{it}$ and ExcessStrike$^H_{it}$ variables are indicators for whether the predicted residual obtained from running the IV regression from Column 3 of Table 2 falls respectively within the medium and highest tercile of residual values. (Age≤48)$_{it}$ and (49≤Age≤53)$_{it}$ are dummy variables for whether the prefecture party secretary is of the respective ages in year t. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

stronger local connections can provide a boost for one's career trajectory.

We undertake a set of robustness checks and additional exploration of our data in Table 10. We focus in this table on turnover as defined by lateral movements, this being the key source of variation behind our baseline results (c.f., Table 9). In Column 1, we control additionally for dummy variables for the terciles of $\Delta(\text{Events}/L)_{it}$; the results here provide reassurance that it is not the raw change in strikes that explains incumbent turnover, but rather whether this change is excessive after taking into account the severity of the export slowdown at the prefecture level. Column 2 considers the possibility that the "Excess Strike" dummies as currently constructed are functions of $ExpShock_{it}$, and so could be picking up higher-order effects of the export shock. To address this, we include terciles of the Bartik rest-of-the-world trade shock on the right-hand side, as these would help in principle to soak up the higher-order effects of the export slowdown, before re-estimating the regression via OLS; our results on the role of "Excess Strikes" remain robust under this check.[56]

We next distinguish between lateral movements that occurred early in the incumbent's tenure (fewer than 3 years) and those that occurred when his/her tenure was relatively mature ($\geq$ 3 years). We find here that the effects of $ExpShock_{it}$ and the "Excess Strike" terciles on the likelihood of a lateral movement are driven by the cases of early movement before the incumbent had accrued three years of service time as a local party secretary (Column 3), with no statistically significant effect estimated for movements that occurred later in one's tenure (Column 4). Bearing in mind that early lateral movements are akin to a *de facto* demotion, this result provides further evidence that weak export conditions and a high level of "excess strikes" are detrimental to an incumbent's career prospects.

In Columns 5-6, we explore whether the effects on incumbent turnover differ systematically across prefectures on the basis of several key initial characteristics (following the earlier analysis in Panel B of Table 8). Specifically, we augment the regression with interaction terms between the "Excess Strike" terciles and the indicator variable for whether the incumbent was between age 49-53 in year t. We find that leaders in this age group had a significantly higher probability of being laterally moved if their prefecture fell into the highest "Excess Strike" tercile (Column 5); at the same time, these leaders were also less likely to be promoted if there was a medium or high level of "excess strikes" under their watch (Column 6). In other words, it was the incumbents in this prime age group for promotion consideration whose career trajectories were most sensitive to the labor-related fallout from the export slowdown.[57] (Note though that we do not find any effects of "Excess Strikes" that vary across prefectures with different initial fiscal resources, as proxied for by fiscal revenues per worker in 2012.)

In sum, the evidence on incumbent tenure lends itself to the interpretation that the higher levels of government in China made active decisions about the retention or replacement of local party secretaries in response to the export slowdown. These decisions were tied (at least in part) to the prefecture leader's performance in maintaining social stability, and moreover exhibited a degree of sophistication: Local leaders were held to account not on the basis of the absolute

[56]Our results are also unaffected if we remove from the sample prefecture positions that are simultaneously ranked as provincial-level or sub-provincial-level appointments, on the grounds that the decisions over these more prominent appointments could be driven by other political considerations.

[57]This relates to the finding in Jia et al. (2015), who establish that the value of political connections and good job performance are higher for younger Chinese officials.

Table 10: Export Shocks and Party Secretary Turnover: Further Exploration and Robustness

Dependent variable:	**Party Secretary Turnover**$_{i,t+1}$					
	Lateral	Lateral	Lateral Tenure$_{i,t+1} < 3$	Lateral Tenure$_{i,t+1} \geq 3$	Lateral	Promotion
	(1) IV	(2) OLS-RF	(3) IV	(4) IV	(5) IV	(6) IV
ExpShock$_{it}$	-0.0506		-0.0794***	0.0294	-0.0443	0.0018
	(0.0309)		(0.0171)	(0.0411)	(0.0344)	(0.0144)
ExcessStrike$_{it}^{M}$: Medium Tercile	0.0855*	0.0809**	0.0581**	0.0214	0.0714	0.0283
	(0.0424)	(0.0361)	(0.0232)	(0.0341)	(0.0784)	(0.0363)
ExcessStrike$_{it}^{H}$: High Tercile	0.1320**	0.1066**	0.0584*	0.0621	0.0763	0.0627
	(0.0593)	(0.0421)	(0.0295)	(0.0491)	(0.0709)	(0.0418)
Δ(Events/L)$_{it}^{M}$: Medium Tercile	-0.0131					
	(0.0450)					
Δ(Events/L)$_{it}^{H}$: High Tercile	-0.0266					
	(0.0644)					
ExpShockROW$_{it}^{M}$: Medium Tercile		0.0023				
		(0.0417)				
ExpShockROW$_{it}^{H}$: High Tercile		-0.0392				
		(0.0433)				
(49$\leq$Age$\leq$53)$_{it}\times$ExcessStrike$_{it}^{M}$					0.0691	-0.1075*
					(0.0770)	(0.0545)
(49$\leq$Age$\leq$53)$_{it}\times$ExcessStrike$_{it}^{H}$					0.2112**	-0.1412**
					(0.0860)	(0.0577)
(FiscalRev/L)$_{i,12}\times$ExcessStrike$_{it}^{M}$					-0.0213	0.0367
					(0.1332)	(0.0507)
(FiscalRev/L)$_{i,12}\times$ExcessStrike$_{it}^{H}$					-0.0639	-0.0294
					(0.1526)	(0.0773)
Lateral Turnover$_{it}$ or Promotion$_{it}$	-0.4728***	-0.4742***	-0.1335***	-0.3387***	-0.4731***	-0.2849***
	(0.0645)	(0.0663)	(0.0414)	(0.0483)	(0.0597)	(0.0604)
Incumbent controls?	Y	Y	Y	Y	Y	Y
Additional time-t controls?	Y	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y	Y
First-stage F-stat	66.85	–	65.60	65.60	138.5	146.8
Observations	822	822	822	822	822	822
R^2	0.5248	0.5205	0.4923	0.5040	0.5338	0.4983

Notes: The dependent variable is a dummy for whether there was a change in prefecture party secretary in year $t+1$ (i.e., one year after the export shock), that is classified respectively as a lateral movement (Columns 1-5), and as a promotion (Column 6). Column 3 further restricts the dependent variable to an indicator for lateral movements that occurred when the incumbent had a tenure of <3 years, while Columns 4 restricts this to lateral movements when the incumbent had a tenure ≥ 3 years. Lateral Turnover$_{it}$ (respectively, Promotion$_{it}$) is an indicator variable for whether a lateral movement (respectively, promotion) occurred in year t. All columns report IV regressions, except Column 2 where an OLS reduced-form is run that includes terciles of the Bartik rest-of-the-world trade shock variables on the right-hand side. All regressions are weighted by the prefecture's working-age population in 2010. The ExcessStrike$_{it}^{M}$ and ExcessStrike$_{it}^{H}$ variables are indicators for whether the predicted residual obtained from running the IV regression in Column 3 of Table 2 falls respectively within the medium and highest tercile of residual values. The Δ(Events/L)$_{it}^{M}$ and Δ(Events/L)$_{it}^{H}$ variables are indicators for whether the change in CLB events per worker had a value that falls respectively within its medium and highest tercile. The incumbent controls used are those from Table 9, namely: tenure, the (Age$\leq$48)$_{it}$ and (49$\leq$Age$\leq$53)$_{it}$ age dummies, a female dummy, an indicator for whether he/she was born in the same province, and whether he/she holds a Masters degree. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

level of labor strikes, but by whether the strike activity could be deemed excessive after taking into consideration information on the severity of the export slowdown in the prefecture.

9 Conclusion

We have undertaken a wide-ranging investigation into the political economy consequences of a negative shock to exports for China. We have documented how the slowdown in world trade in the years after the global financial crisis was associated with an increase in labor-related strikes in Chinese prefectures. Using a shift-share instrumental variables strategy, we have argued that our estimates reflect a causal impact of these export shocks.

In order to better understand the political responses to this unfolding dynamic, we study a simple model that seeks to capture essential features of China's hierarchical political system. In the wake of a negative export shock, the model predicts that "excess strikes" are associated with a greater likelihood that the upper-level government will replace the local incumbent; the threat of removal in turn induces the local incumbent to increase the effort and resources channelled towards bolstering domestic stability.

These political responses are evident in the novel data that we gathered. Our textual analysis of prefecture annual work reports shows that declining exports led to a rising use of "weiwen" phrases, signaling a heightened emphasis on preserving stability as a political priority. More directly, prefecture-level fiscal expenditures were increased, on both public security measures (to safeguard law and order) and social spending (to potentially assuage worker grievances). Last but not least, we find that severe export slowdowns accompanied by an excessively high level of labor-related incidents – in excess of what would be predicted by the extent of the shock to exports – help to explain subsequent turnover of local party secretaries.

These patterns are useful for understanding the political response within China to the recent decline in exports, a topic of obvious importance given China's role in global trade and the world economy. More broadly though, they shed light on how economic shocks impact political outcomes in the context of an autocratic regime with high levels of state capacity: Local incumbents can be removed if they under-perform, but this accountability is exercised within the political system from above, rather than stemming from the ballot box (in the case of democracies) or the threat of political violence (in weak autocracies). With a large and arguably increasing share of the world's population living under strong autocratic regimes, understanding how such political systems function and cope with economic challenges is more relevant than ever.

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A Data Appendix (ONLINE ONLY)

A.1 Labor Disputes Data from MOHRSS

The data on the number of labor dispute cases are from the China Labor Statistical Yearbook, published by the Ministry of Human Resources and Social Security (MOHRSS). These record labor dispute cases that have been officially submitted for mediation or arbitration to "employment dispute arbitration committees" (劳动争议仲裁委员会) at the county level. The count is aggregated at the province level when reported in the statistical yearbooks.

Panel A in Figure A.1 demonstrates that at the national level, the trends over time in the total number of MOHRSS labor dispute cases and the total number of CLB-reported labor events are highly correlated. Panel B shows that this is true too when comparing annual changes in the MOHRSS labor dispute and CLB labor strike variables. Panel C in the same figure confirms that over the 2013-2015 period, the annual changes in both series are positively correlated across provinces. (There is one observation for Ningxia that appears to be an outlier to the right, but removing this point would further strengthen the positive correlation.)

A.2 Night-Lights Data

The night-lights measures are constructed from the Visible Infrared Imaging Radiometer Suite Day/Night Band (VIIRS-DNB) dataset. This provides a monthly average of night-lights intensity in 15 arc-second geographic grids, corresponding to a physical distance of approximately 463 meters. The VIIRS-DNB dataset commences in April 2012, and is based on raw readings obtained and processed from the Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite launched in 2011. The sensors onboard represent an advancement in night-time imaging capacity, that surpasses its predecessor – the Defense Meteorological Program Operational Line-Scan System (DMSP-OLS) – in radiometric accuracy, spatial resolution and geometric quality (Jing et al. 2015). Most existing studies use night-lights intensity data from the DMSP-OLS (see Henderson et al. 2012, for example), but this data is only available up till 2013. With the VIRRS-DNB, we calculate the average night-lights intensity across observation grids that overlap with each Chinese prefecture's territory. VIRRS-DNB does not provide data for Northern China during the summer time as a result of the stray light problem, and so we exclude observations across all prefectures from May to August. Lastly, we aggregate the prefecture-monthly data to the prefecture-annual level.

A.3 Rationalizing the Export-share Weights in the Bartik IV

We provide a brief justification for the use of weights based on initial export shares in the construction of the Bartik IV in (3). Let X_{iR}^{k} denote the value of exports of product k from prefecture i in China to the ROW. We have:

$$X_{iR}^k = \lambda_{iR}^k Y_R^k,$$

where Y_R^k is the total expenditure in the ROW on product k, while λ_{iR}^k is the corresponding expenditure share (out of Y_R^k) that is allocated to those products that originate from prefecture i in China. The value of product-k exports from China as a whole to the ROW, X_{CR}^k, is given by a similar relation:

$$X_{CR}^k = \lambda_{CR}^k Y_R^k,$$

where λ_{CR}^k denotes the expenditure share on those products that originate from China.

Consider now a set of exogenous shocks that shifts the foreign demand for good k. Let X_{iR} denote total exports from prefecture i to the ROW. The change in these total exports is then given by:

$$dX_{iR} = \sum_k \lambda_{iR}^k dY_R^k + d\lambda_{iR}^k Y_R^k = \sum_k \left(\frac{\lambda_{iR}^k}{\lambda_{CR}^k} X_{CR}^k \frac{dY_R^k}{Y_R^k} + \frac{d\lambda_{iR}^k}{\lambda_{iR}^k} X_{iR}^k \right) = \sum_k \left(\frac{X_{iR}^k}{X_{CR}^k} d\tilde{X}_{CR}^k + \frac{d\lambda_{iR}^k}{\lambda_{iR}^k} X_{iR}^k \right).$$

where $d\tilde{X}_{CR}^k = X_{CR}^k \frac{dY_R^k}{Y_R^k}$ is the change in product-k exports from China induced by the demand shock in the ROW. In our empirical approach, we focus on sources of variation in prefecture-i exports to the ROW that stem from shifts in foreign demand conditions. This corresponds precisely to the first set of terms in the above expression for dX_{iR}, namely: $\sum_k \frac{X_{iR}^k}{X_{CR}^k} d\tilde{X}_{CRk}$. The construction of the Bartik IV thus adopts as weights the initial share of prefecture i in China's total exports of product k (i.e., $\frac{X_{iR}^k}{X_{CR}^k}$); in practice, we also replace $d\tilde{X}_{CR}^k$ by the corresponding change in product-k exports from the ROW to the ROW.

A.4 An Example of a "Weiwen" Paragraph

The following is an example of a "weiwen" paragraph that was included in our training sample for the machine learning algorithms. This paragraph is from the State Council document of 13 April 2015, entitled: "Opinions on Strengthening Society's Public Security Prevention and Control System". The extracted paragraph in Chinese and its English translation (lightly edited by Google Translate) are included.

Original:

"健全社会治安形势分析研判机制。政法综治机构要加强组织协调，会同政法机关和其他有关部门开展对社会治安形势的整体研判、动态监测，并提出督办建议。公安机关要坚持情报主导警务的理念，建立健全社会治安情报信息分析研判机制，定期对社会治安形势进行分析研判。加强对社会舆情、治安动态和热点、敏感问题的分析预测，加强对社会治安重点领域的研判分析，及时发现苗头性、倾向性问题，提升有效应对能力。建立健全治安形势播报预警机制，增强群众自我防范意识。"

Translation:

"[We shall] improve the analysis and evaluation system on public security. The procuratorial office, judicial administrative department, and public security department shall work collectively and, in accordance with other departments, carry out all-round dynamic monitoring, and put forward suggestions and advice. The public security department shall uphold intelligence-led policing, establish and enhance the mechanism for analyzing, inspecting, and reviewing criminal intelligence on social stability. [We shall] regularly examine and monitor the public security situation. [We shall] improve the system of analyzing and predicting the trend of social opinions, hotspot security problems, and sensitive issues. [We shall] strengthen the analysis and examination of the major aspects of social stability in order to uncover in a timely manner the emerging and hidden risks that endanger social stability, and to improve the ability to cope with such issues. [We shall] establish and improve the monitoring and early-warning mechanisms for public security, and enhance people's awareness for self-protection."

A.5 Machine Learning Models and Packages

Our machine learning models require inputs of words, commonly known as tokens in the field of natural language processing, for training and classification purposes. Unlike English, where tokenization simply involves splitting the text at white spaces and punctuation marks, Chinese text tokenization is more complicated due to the lack of delimiters such as spaces between words. We employed an open source software library called *jieba* to perform this task; this library contains a large dictionary of Chinese words, along with their relative positions and their respective frequencies.[58] When the software scans through a sentence, it builds a directed acyclic graph (DAG) for all possible word combinations, and then identifies the most probable combination based on the word-position frequency from its dictionary.

For both the Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM) models, we adopted packages from the open source *scikit-learn* library.[59] This is a well-tested and well-supported machine learning software library, with packages written in Python. For the MNB, we used a "term frequency-inverse document frequency" (TFIDF) construction tool to compute the frequencies of word tokens, as a first step in preparing the text documents for analysis.[60]

To operationalize these supervised machine learning algorithms, we put together a training dataset comprising: (i) 20 prefecture annual work reports selected at random from a pre-sample year (2011); and (ii) the State Council document of 13 April 2015 on: "Opinions on Strengthening Society's Public Security Prevention and Control System". For (i), we manually identified the sentences in each of the 20 reports that were on the topic of maintaining social stability ("weiwen"); for (ii), we classified the entire report as being about "weiwen". The

[58] Available at: https://github.com/fxsjy/jieba

[59] See: http://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html, and http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

[60] From: http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html.

MNB model uses this training dataset as the basis for computing a posterior probability that an unseen text passage is about "weiwen", based on a multinomial probability distribution model for the occurrence of tokens; the model is "naive", in that it assumes a zero correlation in the joint occurrence of any pair of tokens. The SVM model on the other hand transforms the passages from the training dataset into points in a high-dimensional metric space, and then partitions these in a binary fashion via a hyperplane that seeks to maximize the distance between itself and the nearest observation that lies on either "side" of it; unseen text passages are then mapped into this same metric space, and classified as "weiwen" or not on the basis of which side of the hyperplane they are located.

In line with common practice, we performed a cross-validation of the 20 pre-sample work reports at the training stage as follows. We divided these into four subsets of 5 reports each, and then trained the machine learning model using the first three of these subsets together with the State Council document from (ii). The trained models were then used to score the passages in the omitted subset of 5 reports that had been marked out as being about "weiwen". We repeated the above procedure a further three times, omitting in turn the second, third and fourth subsets of 5 reports. From this exercise, the simple average of the prediction accuracy rates obtained for the passages in the omitted subset of reports was 0.98 for the MNB and 0.97 for the SVM models respectively, providing validation of the internal consistency of the training sample in identifying "weiwen" passages.

We subsequently applied these two models to the prefecture annual work reports in our sample period of interest (2012-2016). The "weiwen" score under each machine learning model for a given work report was computed as the character-length weighted-average of the paragraph scores from that report.

A.6 Classification of Incumbent Turnover

We classify each instance of incumbent turnover as a promotion, a lateral movement, or being due to other causes (corruption, demotion, retirement, movement to an honorary position). This coding is in turn based on a comparison of the political rank of the individual's new position relative to the old position that he/she vacated.

For most prefectures, the position of party secretary is considered to be at the prefecture (or bureau) level in terms of political rank ("Tingju Ji", 厅局级 in Chinese). We consider a movement to be a promotion if the new position is at the sub-provincial ministerial level ("Fusheng Ji", 副省级; or "Fubu Ji", 副部级) or above. To give some examples of sub-provincial level positions, these include: the provincial vice-governor; provincial vice-party secretary; provincial standing committee member; head of People's Procuratorate and People's Court at the provincial level; etc. Some examples of provincial ministerial level ("Sheng Ji", 省级; or "Bu Ji", 部级) positions are: the provincial governor; provincial party secretary; head of different ministries at the central level; etc.

There are a number of key exceptions to the above coding rules. First, there are 4 prefectures that are also province-level municipalities (Beijing, Shanghai, Tianjin, Chongqing), so the party secretary position is considered a rank at the provincial ministerial level; for these, we consider their movement as a promotion if the new position is at the sub-national level ("Fuguo Ji", or 副国级) or above. Second, there are 15 prefectures that are also sub-province-level municipalities (Changchun, Chengdu, Dalian, Guangzhou, Hangzhou, Harbin, Jinan, Nanjing, Ningbo, Qingdao, Shenyang, Shenzhen, Wuhan, Xi'an, Xiamen), where the party secretary is a rank at the sub-provincial ministerial level; for these, we consider a movement to be a promotion if the new position is at the provincial ministerial level or above. Third, we do not consider movements to positions in the province-level People's Congress or province-level People's Political Consultative Committee to be promotions, since these are viewed as honorary positions akin to "consolation prizes" in China's political hierarchy; this follows Li and Zhou (2005) and Yao and Zhang (2015).

During the period 2014-2016, there were 292 instances of local party secretary turnover, out of 987 available prefecture-year observations. Of these, 73 (or 25%) were classified as promotions and 161 (or 55.1%) as lateral movements. The latter include 50 instances of early lateral movements, that occurred before the incumbent had accrued three years in that position.

Promotion age profile: Figure A.2 presents the age distribution of the prefecture party secretaries (right vertical axis), as well as the observed promotion probability at different ages (left vertical axis). The figure is constructed using the sample of prefecture party secretaries from 2012-2016; note that the promotion probability is computed simply as the share of incumbents promoted at each given age. The figure shows that the promotion likelihood peaks between ages 49-53 and declines steadily afterward. Likewise, the frequency of observing a party secretary at a given age declines after age 53. In our empirical analysis, we thus consider the age range between 49-53 as that in which a prefecture party secretary would see his/her expected future rents from holding office to be at its largest.

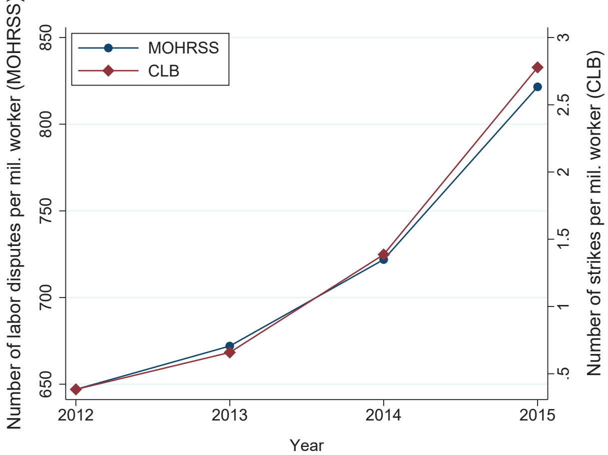
Early lateral movement and career trajectory: We investigate the implications of early lateral movement on an official's career path, to show that this lowers his/her probability of future promotion. Toward this end, we use the data on political turnover of prefecture party secretaries and restrict the sample to those officials who experienced a lateral movement during 2007-2012; we then examine the career path of these officials up until 2016 where our data end.

For each official, we consider the first lateral move he/she experienced in 2007-2012. Let P_0 denote the position that the official held prior to this move, and let P_1 be the position to which he/she was moved laterally. Let P_2 then denote the position that he/she moved to in his/her next subsequent move, if any. We code up a dummy variable equal to 1 if P_2 is a higher political rank relative to P_1; the dummy is equal to 0 otherwise, including in situations where the official did not experience a subsequent move P_2. Figure A.3 illustrates the future promotion probability among these lateral movers, grouped by bins according to their tenure duration in P_0 at the time they were moved to P_1. Notice that the subsequent promotion probability of early lateral movers, i.e., those who were in position P_0 for fewer than three years, is lower than that of lateral movers with a tenure of 3-5 years.

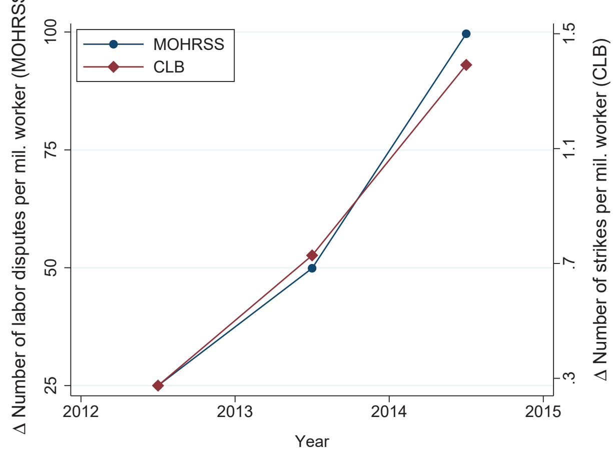
This finding is further substantiated by the regressions reported in Table A.2. Using the same sample of prefecture party secretaries as in Figure A.3, we regress various outcome measures related to future promotion on: (i) dummy variables for the official's years of tenure in P_0 at the time of the lateral move to P_1; and (ii) a set of officeholder control variables, as listed in the Table A.2 footnote. The dependent variables are dummies for whether: (i) the move to P_2 was a promotion relative to P_1 (Column 1); (ii) the official was ever promoted in any moves including and subsequent to P_2 (Column 2); (iii) the highest rank he/she occupied was at the sub-provincial level or higher (Column 3); and (iv) the highest rank he/she occupied was at the provincial level or higher (Column 4). Columns 1 and 2 confirm that early lateral movers (the omitted category) have lower future promotion prospects relative to lateral movers who had spent between 3-6 years in their prior positions. The effect is statistically significant for promotion during one's next move (Column 1); it may even affect one's prospects of ever being promoted (Column 2), at least to the extent observable by 2016, although this coefficient is not statistically significant. Early lateral movers are also less likely to make it to positions higher up the political ranking, specifically to provincial-level positions (Column 4).

Figure A.1: Comparing CLB Labor Events versus MOHRSS Labor Disputes

A. Number of Events (national)



B. Changes in Number of Events (national)



C. Changes in Number of Events (across provinces)

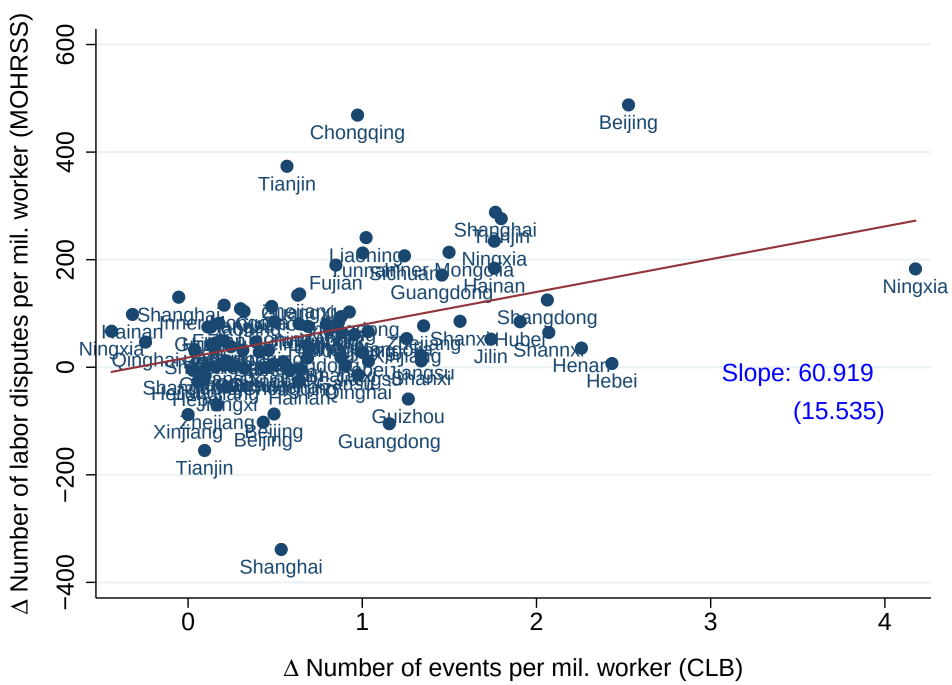


Figure A.2: Promotion Age Profile

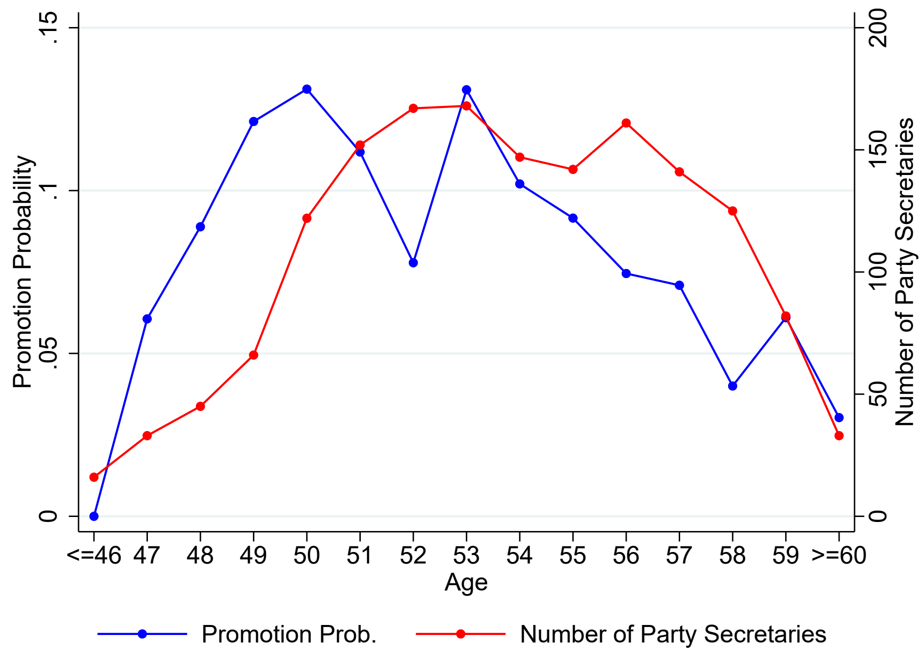


Figure A.3: Future Promotion Probability of Lateral Movers

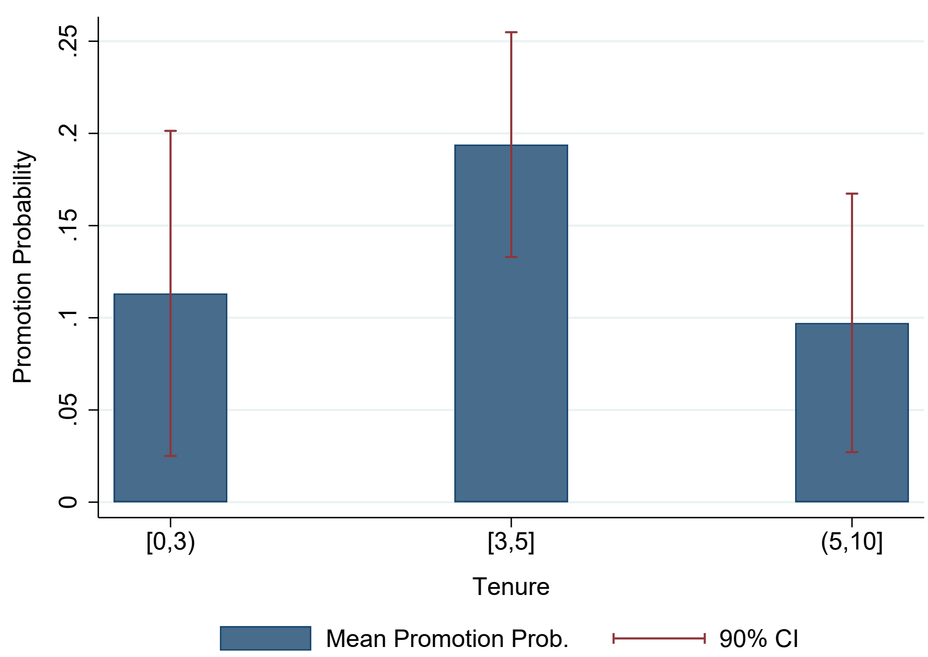


Table A.1: Keywords Related to "preserving stability"

Chinese	English
维稳	a shorthand term for "preserving stability"
维护稳定	preserving stability
保持稳定	maintaining stability
社会稳定	social stability
和谐稳定	harmony and stability
安全稳定	safety and stability
安定和谐	safety and harmony
社会和谐	social harmony
公共安全	public security
和谐平稳	harmony and stability
维稳处突	a shorthand term for "preserving stability and handling sudden-breaking incidents"

Table A.2: Future Promotion Probability of Lateral Movers

Dependent variable:	**Promotion: in the next movement**	**Promotion: ever in the future**	**Highest rank: sub-province level or above**	**Highest rank: province level or above**
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Tenure∈[3,6)	0.1505***	0.0872	0.0119	0.0803*
	(0.0510)	(0.0890)	(0.0847)	(0.0438)
Tenure∈[6,10)	0.0112	-0.0261	0.0460	0.0441
	(0.0705)	(0.1023)	(0.1142)	(0.0358)
Incumbent characteristics?	Y	Y	Y	Y
Year dummies?	Y	Y	Y	Y
Province dummies?	Y	Y	Y	Y
Observations	276	276	276	276
R^2	0.2121	0.1989	0.2601	0.1498

Notes: The sample comprises all prefecture party secretaries who recorded a lateral move during 2007-2012. The incumbent characteristics included as controls are dummy variables for whether (in the lateral-move year) the official: was aged ≤48; was aged 49-53; held a masters degree or higher; is female; held the party secretary position in a prefecture within the same province as his/her birth. All columns also use turnover year dummies and province dummies. Robust standard errors clustered by province are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B Additional Results & Checks (ONLINE ONLY)

B.1 Basic Specification Checks

Table B.1 presents a set of specification checks on our findings linking a slowdown in exports at the prefecture level to increases in labor strikes (Column 1) and responses by the political authorities (Columns 2-5). The dependent variables in this table (and in other robustness tables that follow) are in column order: (i) the time-t change (relative to the previous year) in the number of CLB-recorded strikes per worker; (ii) the time-$(t+1)$ change in the log Multinomial Naive Bayes (MNB) "weiwen" score; (iii) the time-$(t+1)$ change in log fiscal expenditure on public security; (iv) the time-$(t+1)$ change in log fiscal expenditure on social spending; and (v) an indicator variable for party secretary turnover in time $(t+1)$. The IV specifications that are estimated follow equation (2) for Column 1, equation (8) for Columns 2-4, and equation (9) for Column 5.

Panel A in Table B.1 shows that the results remain intact if the province-year fixed effects are replaced by region-year fixed effects.[61] This specification allows us to retain several large prefectures (Beijing, Shanghai, Tianjin, Chongqing) that comprise their entire province, that would otherwise be dropped from the sample when province-year fixed effects are used. The effects of the export shock variable remain robust, except in the final column where the dependent variable is incumbent turnover. Note though that the loss of significance here is driven entirely by one observation, Shanghai; if this were dropped, the coefficient of the export shock variable is -0.0589 with a standard error of (0.0256), which is significant at the 5% level. In Panel B, we drop the additional time-t control variables, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. The estimates here confirm that these auxiliary controls have little bearing for our main results. Panel C reports unweighted regressions, to demonstrate that the findings do not depend on the decision to weight the regressions by prefecture initial workforce size.

Panels D and E demonstrate that the relationships we have uncovered hold too when we focus on cross-prefecture variation. In particular, Panel D runs regressions on a cross-section of observations from the year 2015 only; prefecture fixed effects are thus dropped, but province fixed effects are included. Panel E returns to the full panel, but drops the prefecture fixed effects, while retaining the province-year fixed effects. The results from Panels D and E confirm that our findings do not hinge on exploiting the within-prefecture variation over a short panel, the latter being a setting where the coefficient estimates could potentially be exposed to Nickell bias. In Panel F, we restore the prefecture fixed effects, but drop the lag level of the outcome variable from the right-hand side; the latter is the variable that potentially induces the Nickell

[61] The seven regions are: Northeast (Heilongjiang, Jilin, and Liaoning), North (Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia), Central (Henan, Hubei, and Hunan), East (Shandong, Jiangsu, Anhui, Shanghai, Zhejiang, Jiangxi, and Fujian), South (Guangdong, Guangxi, and Hainan), Northwest (Shannxi, Gansu, Ningxia, Qinghai, and Xinjiang), and Southwest (Sichuan, Guizhou, Yunnan, Chongqing, and Tibet).

bias in this panel regression model. We continue to obtain negative and significant export shock coefficients, except for the "weiwen" textual measure in Column 2. The conclusions that we draw on the effects of the export slowdown is thus robust to the use of these specifications in Panels D-F that would sidestep the issue of Nickell bias.

We moreover argue that the likely direction of bias on the export shock coefficient that might stem from these short-panel concerns would, if anything, lead us to under-state the magnitude of the negative effect of the export slowdown. For the purposes of exposition, we lay this out using $y_{it} = (Events/L)_{it}$, but it should be clear that the argument applies too to the other outcome measures we consider in the paper. The regression specification from (2) with prefecture fixed effects can equivalently be re-written in first-differenced form as follows:

$$\Delta y_{it} - \Delta y_{i,t-1} = \beta_1 \Delta ExpShock_{it} + \beta_2 \Delta y_{i,t-1} + \beta_{\tilde{X}} \Delta \tilde{X}_{it} + \Delta \varepsilon_{it}, \tag{B.1}$$

where we use $\tilde{X}_{it}$ to jointly denote the control variables in X_{it} and the province-time fixed effects D_{pt}; the 'Δ' notation refers to the change in the variable in question relative to the previous year. It is straightforward to show that the OLS estimate of β_1 from (B.1) is given by:

$$\hat{\beta}_1 = \beta_1 - \frac{Cov(\Delta y_{i,t-1}, \Delta \varepsilon_{it}) Cov(\Delta y_{i,t-1}, \Delta ExpShock_{it})}{Var(\Delta y_{i,t-1}) Var(\Delta ExpShock_{it}) - Cov(\Delta y_{i,t-1}, \Delta ExpShock_{it})^2}, \tag{B.2}$$

where it should be understood that the variances and covariances above are being evaluated conditional on the vector of auxiliary variables in $\tilde{X}_{it}$. The denominator on the right-hand side of (B.2) is positive from standard properties of the covariance operator.

First, note that: $Cov(\Delta y_{i,t-1}, \Delta \varepsilon_{it}) = Cov(\Delta y_{i,t-1}, -\varepsilon_{i,t-1}) < 0$, where we have exploited the fact that ε_{it} is orthogonal to past realizations of the outcome variable contained in $\Delta y_{i,t-1}$. Second, we have: $Cov(\Delta y_{i,t-1}, \Delta ExpShock_{it}) = -Cov(\Delta y_{i,t-1}, ExpShock_{i,t-1})$, where we have applied an assumption that $ExpShock_{it}$ is strictly exogenous from the perspective of $\Delta y_{i,t-1}$. In our context, this last covariance term $Cov(\Delta y_{i,t-1}, ExpShock_{i,t-1})$ is plausibly negative, as a lower value of $ExpShock_{i,t-1}$ is likely associated with larger increases in labor strikes. Coming back to (B.2), we can thus conclude that: $\hat{\beta}_1 > \beta_1$; with $\beta_1 < 0$, this implies the fixed effects estimate of the export shock coefficient is likely to be biased in magnitude towards zero.[62]

We turn next to address a different concern, namely the possible presence of influential observations. Toward this end, Figure B.1 presents a residual scatterplot based on the specification reported in Column 3 of Table 2. For the horizontal axis variable, we take the predicted export shock that emerges from running the first-stage of the IV regression; we then regress this predicted variable against the right-hand side variables in equation (2) excluding $ExpShock_{it}$, while weighting the observations by $L_{i,2010}$, in order to extract an export shock residual. The

[62] Given that we obtain in our empirics a robust negative estimate for the coefficient of $ExpShock_{it}$, this points to the covariance between $\Delta y_{i,t-1}$ and $\varepsilon_{i,t-1}$ being small in practice. This could be due to the inclusion of the province-year fixed effects (and other controls) leaving less variation in the residuals against which $\Delta y_{i,t-1}$ might be correlated.

vertical axis variable is analogously constructed, as the residual from regressing the change in CLB events per million workers against all right-hand side variables in (2) while weighting the observations by $L_{i,2010}$, once again excluding $ExpShock_{it}$. The residual scatterplot reveals a downward-sloping relationship, and moreover provides reassurance that no single observation appears to be driving the negative slope.

In Table B.2, we demonstrate that the findings are robust to dropping each province in turn, so that there is no particular province that is driving the results. For each column, the table reports the largest and smallest $ExpShock_{it}$ coefficients obtained from this exercise of dropping one province at a time, together with the associated statistical significance levels.

B.2 Controlling for other Domestic Shocks

A potential concern is that demand shocks from the ROW could be correlated with shocks that originate from within China's prefectures. The estimated export shock coefficient in our regressions may thus be picking up the effects of these domestic demand or supply shocks, rather than the effect of export demand *per se*.

Consider first the possible role of domestic demand shocks. We construct a measure of domestic demand, in order to directly control for it in the regressions. We build this measure from information on absorption (i.e., domestic output less net exports) at the industry level. For each four-digit Chinese Standard Industrial Classification (CSIC) industry (indexed by j) and year (indexed by t), we compute first the output of that industry that is absorbed in the Chinese economy as: $Absorption_{jt} = Output_{jt} - Export_{jt} + Import_{jt}$; in particular, the data on output are from the China Industry Statistical Yearbooks. We then project the annual change in $Absorption_{jt}$ onto Chinese prefectures i using a Bartik-style construction as follows:

$$AbsorptionShock_{it} = \sum_j \frac{L_{ij,2010}}{\sum_i L_{ij,2010}} \frac{\Delta Absorption_{jt}}{L_{i,2010}}.$$

In words, this is a weighted-average measure of the industry-level absorption shocks, where the weights used are the initial shares of prefecture i in China-wide employment in industry j (i.e., $L_{ij,2010}/\sum_i L_{ij,2010}$); these weights are computed from the 2010 China Annual Survey of Industrial Firms. The variable is further normalized by the working age population in prefecture i, $L_{i,2010}$ (from the 2010 Census). This is the proxy for domestic demand shocks at the prefecture level which we control for in Panel A of Table B.3. (We build this measure from industry-level data for China as a whole, as detailed data on industry-level output by prefecture are not yet publicly available for the years in our sample, to the best of our knowledge.)

To control for the role of domestic supply shocks, we construct an analogous Bartik-style measure of prefecture-level shifts in output, using the same data sources as above:

$$OutputShock_{it} = \sum_j \frac{L_{ij,2010}}{\sum_i L_{ij,2010}} \frac{\Delta Output_{jt}}{L_{i,2010}}.$$

We control for this proxy for domestic supply shocks in Panel B of Table B.3; in Panel C, we control for it together with the domestic absorption shock.

Throughout Panels A-C, we find that the estimated effect of the export shock on labor strikes and political responses is similar to the baseline results in the main paper, suggesting that domestic shocks are not influencing our findings. (Interestingly, Column 1 indicates that a weakening in domestic demand and output would be associated with increases in labor strikes, although this does not detract from the strong findings on the role of the export shock.) In Figure B.2, we illustrate the cross-industry correlation between $\Delta Absorption_{jt}$ and $\Delta Output_{jt}$ on the one hand, and the CSIC industry-level export shock on the other. These partial scatterplots are based on data from 2013-2015, and are obtained after residualizing $\Delta Absorption_{jt}$, $\Delta Output_{jt}$, and the CSIC industry-level export shock for the role of year fixed effects. The slope coefficients in the figure are slightly positive, but not different from zero in a statistically significant way. This provides further reassurance that the export shock is not likely to be picking up an incidental correlation with domestic demand or supply shifts.

To assess the potential confounding effect of imports, we construct a Bartik-style measure of prefecture-level import shocks as:

$$ImpShock_{it} = \sum_j \frac{L_{ij,2010}}{\sum_i L_{ij,2010}} \frac{\Delta M_{jt}}{L_{i,2010}},$$

where ΔM_{jt} is the change in imports of industry j in year t, computed from the China customs data. While we are reasonably confident about the exogeneity of external demand shocks faced by Chinese exporters, it is more challenging to propose exogenous import supply shocks to instrument for changes in imports at the prefecture level. With this caveat in mind, Panel D of Table B.3 presents a specification where we introduce the above $ImpShock_{it}$ variable. The estimated export shock coefficient resembles that from the baseline estimates, while the coefficient on the import shock is not statistically significant.

B.3 Alternative Bartik Shocks

In this next set of checks reported in Table B.4, we confirm the robustness of the findings under alternative constructions of the Bartik IV.

Excluding intermediary firms: In Panel A, we drop firms f that are trade intermediaries, identifying these on the basis of their Chinese character firm names, following Ahn et al. (2011). We remove these intermediaries from the construction of the $ExpShock_{it}$ variable in (1) and the ROW Bartik IV in (3).

Destination-specific demand shocks: In Panel B, we use information on the composition of exports across destination markets, to construct the following alternative Bartik IV:

$$\sum_k \sum_{d \neq CHN} \frac{X_{idk,2010}}{\sum_i X_{idk,2010}} \frac{\Delta X^{ROW}_{dkt}}{L_{i,2010}}. \tag{B.3}$$

Here, ΔX_{dkt}^{ROW} denotes the change in exports of product k from the ROW (excluding China) to country d in year t. $X_{idk,2010}/\sum_i X_{idk,2010}$ is the share of exports of product k from China to destination d that originate from prefecture i in the base year (2010); specifically, we apportion destination-specific demand changes to each prefecture according to the initial distribution of exports across source prefectures. The apportioned export shocks are summed across products and destination markets, and then normalized by the local working age population. The variation in (B.3) thus stems from cross-destination-by-product differences in demand shocks, and cross-prefecture differences in initial specialization patterns in producing for different markets. (We exclude exports to Hong Kong and Macau for this exercise.)

Gravity-based Demand Shocks: In Panels C and D, we use an empirical gravity model of trade, in order to extract a component of the shift in trade flows that can be attributed to foreign demand forces. Following Redding and Venables (2004), we first estimate:

$$\ln X_{odkt} = \alpha_1 \ln Dist_{od} + \alpha_2 B_{od} + \alpha_3 Col_{od} + \alpha_3 Lang_{od} + \varphi_{okt} + \varphi_{dkt} + \varepsilon_{odkt}, \tag{B.4}$$

where X_{odkt} denotes the trade flow of product k from country o to country d in year t. On the right-hand side, $Dist_{od}$ is the bilateral distance between o and d; B_{od} is an indicator variable for whether the two countries share a common border; Col_{od} is an indicator variable for shared colonial ties; and $Lang_{od}$ is a common language dummy. (Both the data on bilateral trade flows and distance variables are from the CEPII; we use in particular the BACI database for trade flows.) In the above, φ_{okt} denotes exporter-by-product-by-year fixed effects, while φ_{dkt} denotes importer-by-product-by-year fixed effects; the estimation thus separates import demand from export supply forces, and we consider the φ_{dkt}'s as capturing demand shifters in the ROW that would be faced by Chinese exporters. We estimate (B.4) separately for each HS6-digit product, while excluding trade flows associated with China. We then construct the following measure of exposure to demand shocks in the ROW:

$$\sum_k \sum_{d \neq CHN} \frac{X_{idk,2010}}{\sum_i X_{idk,2010}} \frac{\Delta \hat{X}_{dkt}^{ROW}}{L_{i,2010}}, \tag{B.5}$$

where $\Delta \hat{X}_{dkt}^{ROW} = X_{dk,t-1}^{ROW} \Delta \varphi_{dkt}$. Note that by multiplying the change (in log form) in the product-specific demand shock in d ($\Delta \varphi_{dkt}$) with lagged product-k exports from the ROW to country d ($X_{dk,t-1}^{ROW}$), we obtain the change in exports from the ROW to d as predicted by a gravity-based estimate of the change in market capacity of importer d. Panel C makes use of this gravity-based Bartik IV from (B.5).

We also construct a second gravity-based measure that is analogous to our baseline IV from equation (3) in the main paper:

$$\sum_k \frac{X_{ik,2010}}{\sum_i X_{ik,2010}} \frac{\Delta \hat{X}_{kt}^{ROW}}{L_{i,2010}}. \tag{B.6}$$

Here, $\Delta \hat{X}_{kt}^{ROW} = \sum_{d \neq CHN} X_{dk,t-1}^{ROW} \Delta \varphi_{dkt}$ captures the implied demand shock for product k summed across all destination countries d in the ROW. Panel D makes use of this alternative gravity-based Bartik IV defined in (B.6).

Based on Export Growth Rates: In Panel E, we experiment with a measure of the ROW demand shock that is based on product-level export growth rates, as opposed to being denominated in dollar units per worker. This is constructed as:

$$\kappa_i \sum_k \frac{X_{ik,2010}}{\sum_k X_{ik,2010}} \Delta \ln X_{kt}^{ROW}, \tag{B.7}$$

where $\Delta \ln X_{kt}^{ROW}$ is the product-level growth rate of exports from the ROW to the ROW. Note that the weights $X_{ik,2010}/\sum_k X_{ik,2010}$ are now the share of product k in total exports from prefecture i, and thus capture how important product k is for the prefecture. The term κ_i is a scaling term to capture the importance of exports for economic outcomes in the prefecture; in particular, we set κ_i to be total prefecture exports in 2012 divided by the working age population in 2000 ($X_{i,2012}/L_{i,2000}$). The above variable is in the same spirit as Aghion et al. (2018), who construct a Bartik-style export demand shock measure at the firm level. (To accommodate the zero observations in the product-level trade data, we use the Davis-Haltiwanger-Schuh approximation of the log growth rate, i.e., $\Delta \ln X_{kt}^{ROW} \approx 2\left(\frac{X_{kt}^{ROW} - X_{k,t-1}^{ROW}}{X_{kt}^{ROW} + X_{k,t-1}^{ROW}}\right)$, to avoid dropping observations where X_{kt}^{ROW} or $X_{k,t-1}^{ROW}$ is a zero.) The results from using (B.7) as a Bartik IV for $ExpShock_{it}$ are reported in Panel E. There is a decrease in the first-stage F-statistic to levels that are just above the rule-of-thumb value of 10 for instrument relevance; that said, the effects of the export shock on labor strikes and in inducing political responses from the local government remain statistically significant.

B.4 Dropping One HS Section at a Time

We assess whether our results hinge on the variation in export patterns inherent in any particular segment of products. To do so, we reconstruct both the export shock in (1) and the Bartik IV in (3), but leaving out the products from one HS section at a time. Bear in mind that the HS sections are broad – there are only 15 HS sections – so that the number of products dropped each time is large; there is thus a meaningful amount of variation left out with each iteration of this check.[63] If our baseline results are driven by endogeneity or pre-trend concerns that are associated with a particular sector – a concern articulated by Goldsmith-Pinkham et al. (2018) related to the use of Bartik instruments – one should expect the regression estimates to be sensitive when we drop all products from the corresponding HS section. For each dependent variable, we obtain 15 estimates of the export shock coefficient; we report the range of these

[63] The HS sections are: (i) Animal & Animal Products; (ii) Vegetable Products; (iii) Foodstuffs; (iv) Mineral Products; (v) Chemical & Allied Industries; (vi) Plastics/Rubbers; (vii) Raw Hides, Skins, Leather & Furs; (viii) Wood & Wood Products; (ix) Textiles; (x) Footwear/Headgear; (xi) Stone/Glass; (xii) Metals; (xiii) Machinery/Electrical; (xiv) Transportation; and (xv) Miscellaneous.

coefficients in Table B.5. Across the columns, we always find that the largest and smallest coefficients obtained are negative and significantly different from zero. These findings alleviate the concern that there may be particularly pivotal or influential product segments for which the orthogonality conditions required for identification may be more questionable.

B.5 Effects of Future Export Shocks

To address the possibility that the results might be driven by pre-trends in the key variables, we examine in Table B.6 whether the export shock at time $t+1$ (as opposed to time t) has explanatory power over the outcomes of interest. In particular, we adopt the same IV specifications as in equations (2), (8) and (9), but replace $ExpShock_{it}$ by $ExpShock_{i,t+1}$, while instrumenting for the latter with the time-$(t+1)$ Bartik variable. In Column 1, this means that we examine whether the annual change in strikes per worker in year t (for the sample period 2013-2015) can be explained by the future export shock in year $(t+1)$; in Columns 2-5, we are exploring whether the political response measures observed in year t (for the sample period 2014-2016) respond with no lag to the contemporaneous year-t export shock. Across the columns, the export shock coefficient that we now estimate is smaller in magnitude than in the baseline results and typically not statistically significant. (The only exception is in Column 4, which reports a mildly significant but positive effect on social spending; if anything, one would need a reversion in pre-trends to rationalize the pattern for this particular outcome variable.) In sum, these findings suggest that prefectures hit by more negative exports shocks were not already experiencing faster deterioration in labor market conditions and social stability.

B.6 Balance Test of Product-level Export Shocks

The Bartik IV can be formulated more generally as $\sum_k s_{ik} g_k$, where g_k denotes the export shock experienced by product k and s_{ik} measures the exposure of location i to each product-level shock. (In our context, based on equation (3), we have: $g_k = \Delta X_{kt}^{ROW} / \sum_i X_{ik,2010}$, and $s_{ik} = X_{ik,2010}/L_{i,2010}$.) As discussed in Borusyak et al. (2018), the validity of the instrument relies on the assumption that $\sum_k s_k g_k \phi_k \xrightarrow{\text{p}} 0$, where $s_k = E(s_{ik})$ measures the expected exposure to product k, and $\phi_k = E(s_{ik}\varepsilon_i)/E(s_{ik})$ is an exposure-weighted expectation of untreated potential prefecture-level outcomes. Put in other words, the identification relies on the assumption that, weighted by s_k, the correlation between product-level shocks g_k and unobservables ϕ_k approaches zero in large sample; this is the sense in which the shocks would then be as good as randomly assigned. In our context, this assumption could be violated if say export demand decreased more in products that happen to be produced in prefectures that were hit by other unobserved shocks that also affect social stability.

To allay this concern, we follow Borusyak et al. (2018) to test for whether the export shocks are balanced with respect to various initial prefecture characteristics that could in principle enter the ε_i. In particular, we regress g_{kt} on the empirical counterpart of $\phi_k = E(s_{ik}\varepsilon_i)/E(s_{ik})$, where ε_i comprises a set of various prefecture characteristics from 2010, namely: the share of workers with college education, manufacturing employment share, export-to0GDP ratio, share of population without hukou rights, log GDP per capita, log fiscal revenue per capita. (The data are drawn from the Census, the China City Statistical Yearbook, and the prefecture-level yearbooks.) Table B.7 reports the results of this balance test. We report here the coefficient estimates from regressing the g_{kt}'s (at the HS 6-digit level) against each of the weighted-average prefecture characteristics and year fixed effects (with the sample period being 2013-2015). Each regression is weighted by average industry exposure s_k, and the standard errors are clustered by 4-digit HS codes. The lack of statistical significance of the coefficients, both individually and jointly, provides supportive evidence that our empirical setting – and in particular, the HS 6-digit product-level ROW export shocks – meets the requirements for treatment balance.

B.7 Alternative Clustered Standard Errors

As pointed out in Adão et al. (2019), the regression residuals in shift-share empirical specifications would be correlated across regions that are similar in their sectoral composition, regardless of their geographic proximity, in the presence of unobserved sectoral shifters that affect the outcome of interest. As a result, standard errors that are clustered by geographic unit (in our context, by province) are likely biased downward. To address this potential problem, we construct alternative clusters based on the similarity of prefectures' export structure. For each prefecture, we calculate an index of the similarity of its initial vector of product-level export shares to that of each of the 30 provincial capitals. The index we use is based on Finger and Kreinin (1979):

$$SimilarityIndex_{ij}^{ROW} = \sum_k \min\left\{\frac{X_{ik}^{ROW}}{X_i^{ROW}}, \frac{X_{jk}^{ROW}}{X_j^{ROW}}\right\},$$

where X_{ik}^{ROW}/X_i^{ROW} (respectively, X_{jk}^{ROW}/X_j^{ROW}) denotes product k's share in the total exports of prefecture i (respectively, j) to the ROW. By construction, the index ranges between 0 to 1. If i's and j's export patterns are totally dissimilar, in that i only exports products that j does not (and vice versa), then the index takes on a value of 0. On the other extreme, if the export shares of the two prefectures are identical, then the index is equal to 1. We used the 2010 China customs data to construct this index, and then assigned each prefecture to an export-similarity cluster corresponding to the provincial capital with which its export profile was most similar.

In Table B.8, we report the robust standard errors under different modes of clustering. Row (i) reproduces our baseline standard errors, that are clustered at the province level. Row (ii) reports the standard errors clustered instead by export-similarity group. Row (iii) then presents standard errors that are two-way clustered by province and by export-similarity group. In Rows (iv) and (v), we repeat the exercise in Rows (ii) and (iii), but modify how the export-similarity groups are constructed; specifically, we group each prefecture with the provincial capital outside of its own province with which its export-similarity index is highest. With this, there is no overlap in the clusters at the province level and the export-similarity groups. The statistical inference that we draw is robust regardless of the mode of clustering.

As discussed in Adão et al. (2019), the spatial correlation of regression residuals induced by similarity in sectoral composition will be less of a concern when the number of industries (in our case, products) in the shift-share IV is large, and when the shifter (in our case, export demand from the ROW) soaks up most of the sectoral shocks affecting the outcomes of interest. For our analysis, the number of products is more than 4,000. At the same time, the *annual* product-level export shocks that we exploit can be relatively large in magnitude. These features of our data potentially explain why our statistical inference is robust under alternative ways of clustering the standard errors. (Note that we cannot directly apply the standard-error correction approach proposed in Adão et al. (2019), since the number of products is larger than the number of prefectures (333) in our setting.)

B.8 Political Response to Export Shocks: Details

In this appendix section, we fill in a key detail related to the solution of the model from Section 6 of the main paper. Specifically, we prove that for an upper-level government whose objective is to maximize expected stability, i.e., $E(y) = p(1-x)s_G + (1-p)(1-x)s_B + x$, the optimal decision rule given the export shock x takes the form of a single threshold, with the local leader being retained if and only if the observed y exceeds a cutoff $\bar{y}(x)$.

Recall that stability is given by: $y = x + (1-x)s + \varepsilon$. As ε is an iid $N(0, \sigma^2)$ stochastic term, the realized values of y span the real line. We thus consider decision rules that partition the real line into measurable subsets, and that specify one course of action ("retain" or "replace") that would apply to all stability values that fall within each respective subset. Let y_i where $i \in \{\dots, -1, 0, 1, \dots\}$ denote the sequence of points on the real line that partition out these subsets, such that y_i is increasing in i and adjacent intervals on the real line are associated with different courses of action; in other words, if $(y_j, y_{j+1}]$ is an interval of stability values where the upper-level government decides to retain the local incumbent (where j is an integer), then $(y_{j-1}, y_j]$ and $(y_{j+1}, y_{j+2}]$ are intervals in which the local incumbent will be replaced. Note that the y_i's are each in principle functions of the observed export shock x, but we have suppressed this in the notation. We adopt the convention that if there are only a countably finite number I of cutoffs with index $i < 0$, then $y_{-I-1}, y_{-I-2}, \dots = -\infty$; likewise, if there are only a countably finite number I of cutoffs with index $i > 0$, then $y_{I+1}, y_{I+2}, \dots = \infty$. Without loss of generality, we fix $(y_0, y_1]$ to be an interval in which the upper level government decides to retain the local incumbent.

The objective function of a local leader of type ℓ is thus to maximize:

$$\begin{aligned}
&\left(\sum_{i=\ldots-2,0,2,\ldots} Pr(y_i < y < y_{i+1})\right) R - g_\ell(s) \\
= &\left(\sum_{i=\ldots-2,0,2,\ldots} \Phi(y_{i+1} - x - (1-x)s) - \Phi(y_i - x - (1-x)s)\right) R - g_\ell(s),
\end{aligned}$$

and the associated first-order condition is:

$$\left(\sum_{i=\ldots-2,0,2,\ldots} \phi(y_i - x - (1-x)s) - \phi(y_{i+1} - x - (1-x)s)\right)(1-x)R \;=\; g'_\ell(s). \quad \text{(B.8)}$$

We show first that a type-B local incumbent would have no incentive to choose a positive level of stability-enhancing measures with the functional forms from Section 6. Recall that $g'_B(s) = a_B + \delta s$ and $a_B > R/\sqrt{2\pi\sigma^2}$, so that the type-$B$ leader's marginal cost of effort always exceeds $R/\sqrt{2\pi\sigma^2}$. We in turn show that the marginal benefit on the left-hand side of (B.8) is always smaller than $R/\sqrt{2\pi\sigma^2}$. Note that given x and s, there exists an integer j such that $y_j - x - (1-x)s \leq 0 < y_{j+1} - x - (1-x)s$. We will lay out the proof for the case that j is even, but it should be clear that the proof for the case where j turns out to be odd is analogous since the $\phi(\cdot)$ function is symmetric about 0. The term on the left-hand side of (B.8) that pre-multiplies $(1-x)R$ can be written as:

$$\begin{aligned}
&\left(\sum_{k=1}^{\infty} \phi(y_{j-2k} - x - (1-x)s) - \phi(y_{j-2k+1} - x - (1-x)s)\right) + (\phi(y_j - x - (1-x)s)) \\
&+ \left(\sum_{k=1}^{\infty} \phi(y_{j+2k} - x - (1-x)s) - \phi(y_{j+2k-1} - x - (1-x)s)\right) \quad \text{(B.9)}
\end{aligned}$$

For each $k = 1, 2, \ldots$, we have $\phi(y_{j-2k} - x - (1-x)s) - \phi(y_{j-2k+1} - x - (1-x)s) \leq 0$, since $y_{j-2k} - x - (1-x)s \leq y_{j-2k+1} - x - (1-x)s \leq 0$; note that all these weak inequalities bind as equalities if and only if $y_{j-2k} = y_{j-2k+1} = -\infty$. Also, $\phi(y_{j+2k} - x - (1-x)s) \leq \phi(y_{j+2k-1} - x - (1-x)s)$, since $y_{j+2k} - x - (1-x)s \geq y_{j+2k-1} - x - (1-x)s \geq 0$; once again, this all holds with equality if and only if $y_{j+2k} = y_{j+2k-1} = \infty$. (In particular, the proof as written up admits for the possibility that $(y_j, y_{j+1}] = (y_j, \infty]$ or $(y_j, y_{j+1}] = (-\infty, y_{j+1}]$.) It follows that the expression in (B.9) is less than or equal to $\phi(y_j - x - (1-x)s)$, with equality holding if and only if j is the only cutoff. But $\phi(y_j - x - (1-x)s)$ achieves a maximum value of $1/\sqrt{2\pi\sigma^2}$ precisely when $y_j - x - (1-x)s = 0$. Since $(1-x)R \leq R$, it follows that the left-hand side of (B.8) is indeed not larger than $R/\sqrt{2\pi\sigma^2}$. Thus, (B.8) is never satisfied with equality for $\ell = B$, and we have a corner solution at $s^*_B = 0$.

The upper-level government's problem therefore boils down to enacting a decision rule to elicit as high a level of s_G from G-type leaders as possible, since this is clearly what would maximize $E(y)$. The first-order condition for G-type leaders is given by (B.8) with $\ell = G$, and with $g'_G(s) = \delta s$. Since this is increasing in s (i.e., the cost function is convex), the upper-level government will seek a decision rule that pushes up the value of the left-hand side of (B.8) as much as possible, so that the G-type incumbent will in turn set a high value of s_G. As we have just seen from the argument above, the left-hand side of (B.8) achieves a maximum value of $(1-x)R/\sqrt{2\pi\sigma^2}$ if and only if j is the only cutoff and $y_j - x - (1-x)s = 0$; the presence of any other cutoffs would lower the left-hand side of (B.8). It follows that the optimal decision rule features a unique cutoff $y_j = x + (1-x)s_G$, where the upper-level government replaces the local incumbent when stability y falls below y_j and retains him when y is larger than y_j.

Note that s_G is in turn determined by solving the G-type incumbent's first-order condition bearing in mind the nature of the threshold rule that the upper-level government will adopt. At $s = 0$, the marginal benefit for the G-type incumbent to enacting stability-enhancing measures, given by the left-hand side of (B.8), is clearly positive; this exceeds the marginal cost, which is 0 at $s = 0$. On the other hand, as s tends to infinity, the marginal cost increases without bound, while the marginal benefit term is bounded above by $(1-x)R/\sqrt{2\pi\sigma^2}$. This implies the existence of an interior solution to the G-type leader's first-order condition. The solution is in fact unique, with the closed-form expression for s_G derived in the main paper and given by (6).

Figure B.1: Residual Scatterplot
(based on Column 3, Table 2)

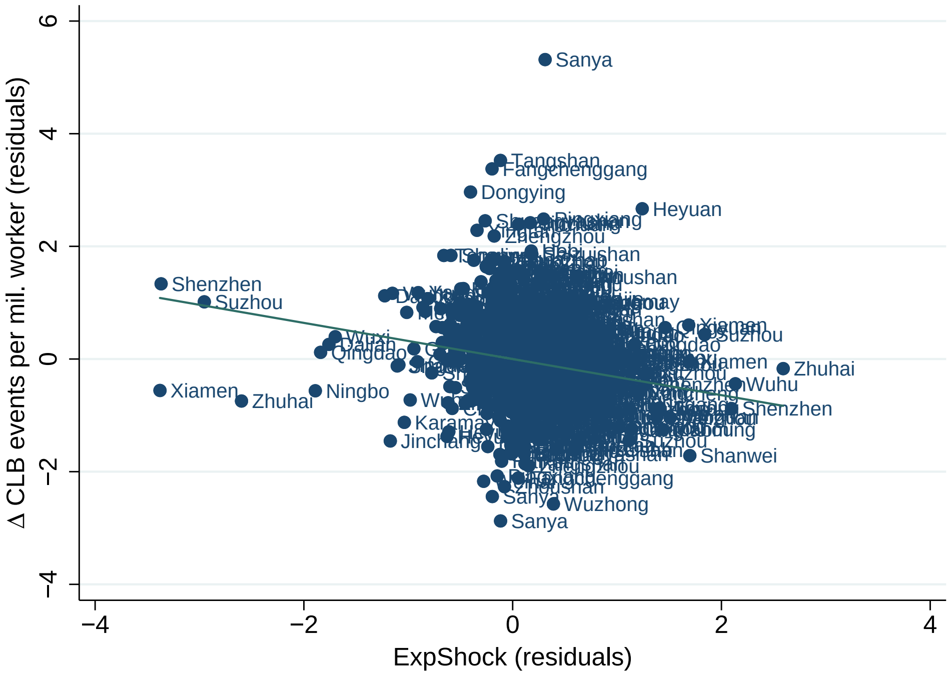


Figure B.2: Cross-Industry Correlation between Domestic Demand, Domestic Output and Export Shocks

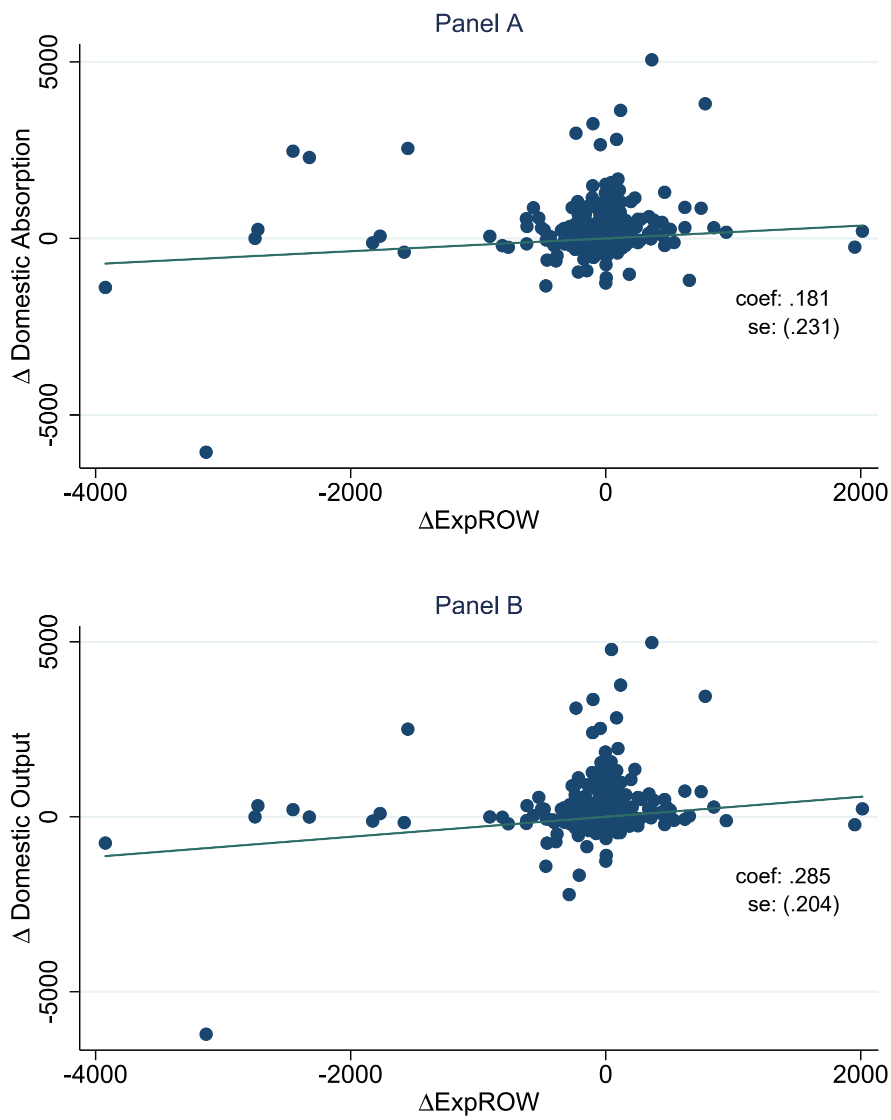


Table B.1: Robustness: Basic Specification Checks

Dependent variable:	**Δ CLB Events per million**$_{it}$	**Δ Log MNB "weiwen" score**$_{i,t+1}$	**Δ Log Fiscal Public Security**$_{i,t+1}$	**Δ Log Fiscal Social Spending**$_{i,t+1}$	**Party Secretary Turnover**$_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Panel A: Region×Year FEs				
ExpShock$_{it}$	-0.2210***	-0.2181**	-0.0159***	-0.0292***	-0.0186
	(0.0740)	(0.0793)	(0.0054)	(0.0087)	(0.0436)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Region-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	50.05	50.97	75.24	75.06	66.53
Observations	837	817	827	778	837
R^2	0.5783	0.4616	0.6839	0.7063	0.5089
	Panel B: Drop Additional Time-t Controls				
ExpShock$_{it}$	-0.3190***	-0.1600**	-0.0231***	-0.0173**	-0.0596***
	(0.0560)	(0.0772)	(0.0072)	(0.0067)	(0.0163)
Additional time-t controls?	N	N	N	N	N
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	49.20	52.63	69.06	101.0	58.64
Observations	987	923	958	906	975
R^2	0.6105	0.5022	0.7629	0.7697	0.5364
	Panel C: Unweighted Regressions				
ExpShock$_{it}$	-0.2504***	-0.1484*	-0.0212**	-0.0085**	-0.0711***
	(0.0818)	(0.0753)	(0.0079)	(0.0032)	(0.0224)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	52.13	45.59	53.61	65.36	52.79
Observations	822	802	812	760	822
R^2	0.6513	0.5395	0.7654	0.7309	0.5660

Table B.1: Robustness: Basic Specification Checks (cont.)

Dependent variable:	**Δ CLB Events per million**$_{it}$	**Δ Log MNB "weiwen" score**$_{i,t+1}$	**Δ Log Fiscal Public Security**$_{i,t+1}$	**Δ Log Fiscal Social Spending**$_{i,t+1}$	**Party Secretary Turnover**$_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Panel D: Cross-section (2015 only)				
ExpShock$_{it}$	-0.4393***	-0.1116***	-0.0206*	-0.0220**	-0.0397†
	(0.1132)	(0.0357)	(0.0103)	(0.0085)	(0.0268)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	N	N	N	N	N
Province dummies?	Y	Y	Y	Y	Y
First-stage F-stat	188.1	131.2	120.3	143.5	160.7
Observations	277	275	273	265	277
R^2	0.2332	0.2884	0.4023	0.3495	0.3309
	Panel E: Cross-section (2013-2015 pooled)				
ExpShock$_{it}$	-0.2495***	-0.1407**	-0.0211**	-0.0267**	-0.0543***
	(0.0824)	(0.0557)	(0.0084)	(0.0104)	(0.0182)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	N	N	N	N	N
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	116.5	102.6	130	140.8	134.2
Observations	825	807	817	771	825
R^2	0.3297	0.3449	0.4848	0.4436	0.2679
	Panel F: Drop Lag Level Controls				
ExpShock$_{it}$	-0.1728**	-0.0358	-0.0235***	-0.0293***	-0.0461**
	(0.0746)	(0.0936)	(0.0069)	(0.0093)	(0.0189)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	105.6	106.4	107.1	134.2	85.54
Observations	822	802	812	760	822
R^2	0.5264	0.2800	0.6095	0.5879	0.3919

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Panel A uses region-year instead of province-year fixed effects. Panel B drops the additional time-t controls (i.e., the changes in the log college-enrolled, mobile-use, and internet-use shares). Panel C reports unweighted regressions, instead of weighting by the prefecture 2010 working-age population as in the rest of the table. Panel D reports a cross-sectional regression using data from 2015 only; province fixed effects are used in lieu of province-year and prefecture fixed effects. Panel E uses the full sample from 2013-2015; province-year fixed effects are used, but the prefecture fixed effects are dropped. Panel F drops the time-$(t-1)$ level of CLB events per million workers or the corresponding time-t level of the political response measures from the right-hand side. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, † < 0.15.

Table B.2: Robustness: Dropping One Province at a Time

Dependent variable:	**Δ CLB Events per million**$_{it}$	**Δ Log MNB "weiwen" score**$_{i,t+1}$	**Δ Log Fiscal Public Security**$_{i,t+1}$	**Δ Log Fiscal Social Spending**$_{i,t+1}$	**Party Secretary Turnover**$_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Range of Estimates:					
Min ExpShock$_{it}$ coef.	-0.3650***	-0.2436†	-0.0276***	-0.0191***	-0.0864***
	(0.1095)	(0.1514)	(0.0063)	(0.0063)	(0.0157)
Max ExpShock$_{it}$ coef.	-0.3022***	-0.1319***	-0.0164†	-0.0072*	-0.0666***
	(0.0476)	(0.0453)	(0.0102)	(0.0041)	(0.0242)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. For each dependent variable, the regressions are run dropping each province in turn; the smallest and largest export shock coefficients with associated standard errors are reported. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table B.3: Robustness: Controlling for Other Prefecture-Level Shocks

Dependent variable:	**Δ CLB Events per million$_{it}$**	**Δ Log MNB "weiwen" score$_{i,t+1}$**	**Δ Log Fiscal Public Security$_{i,t+1}$**	**Δ Log Fiscal Social Spending$_{i,t+1}$**	**Party Secretary Turnover$_{i,t+1}$**
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Panel A: Domestic Absorption Shocks				
ExpShock$_{it}$	-0.2303***	-0.2393**	-0.0232***	-0.0186**	-0.0746**
	(0.0679)	(0.1045)	(0.0060)	(0.0071)	(0.0272)
AbsorptionShock$_{it}$	-0.2399*	0.1206	0.0043	0.0071	0.0009
	(0.1299)	(0.0982)	(0.0055)	(0.0063)	(0.0367)
First-stage F-stat	51.12	47.93	64.79	95.50	54.46
Observations	822	802	812	760	822
R^2	0.6655	0.5096	0.7726	0.7787	0.5470
	Panel B: Domestic Output Shocks				
ExpShock$_{it}$	-0.2062**	-0.1740***	-0.0224***	-0.0213***	-0.0504†
	(0.0837)	(0.0583)	(0.0045)	(0.0051)	(0.0328)
OutputShock$_{it}$	-0.2075*	-0.0278	0.0016	0.0096**	-0.0398
	(0.1059)	(0.0543)	(0.0077)	(0.0041)	(0.0550)
First-stage F-stat	24.71	22.02	24.57	34.37	21.45
Observations	822	802	812	760	822
R^2	0.6671	0.5167	0.7735	0.7756	0.5564
	Panel C: Domestic Absorption & Domestic Output Shocks				
ExpShock$_{it}$	-0.2190***	-0.1436***	-0.0217***	-0.0216***	-0.0420
	(0.0768)	(0.0489)	(0.0044)	(0.0041)	(0.0295)
AbsorptionShock$_{it}$	-0.1943	0.5172	0.0100	-0.0051	0.1293
	(0.1535)	(0.3564)	(0.0148)	(0.0140)	(0.0965)
OutputShock$_{it}$	-0.0517	-0.4355	-0.0062	0.0134	-0.1423
	(0.0857)	(0.3024)	(0.0175)	(0.0109)	(0.1173)
First-stage F-stat	22.79	21.09	23.12	34.07	20.25
Observations	822	802	812	760	822
R^2	0.6669	0.5339	0.7748	0.7752	0.5620
	Panel D: Import Shocks				
ExpShock$_{it}$	-0.3151***	-0.1947**	-0.0215***	-0.0152**	-0.0798***
	(0.0550)	(0.0803)	(0.0077)	(0.0058)	(0.0249)
ImpShock$_{it}$	-0.1259	0.0888	0.0033	-0.0148	0.1174
	(0.3743)	(0.2260)	(0.0179)	(0.0138)	(0.1178)
First-stage F-stat	118.0	135.1	239.0	224.3	180.6
Observations	822	802	812	760	822
R^2	0.6476	0.5142	0.7746	0.7821	0.5463
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. The prefecture-level absorption, output, and import shocks are constructed as described in Section B.2. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table B.4: Robustness: Alternative Bartik Measures

Dependent variable:	Δ CLB Events per million$_{it}$ (1) IV	Δ Log MNB "weiwen" score$_{i,t+1}$ (2) IV	Δ Log Fiscal Public Security$_{i,t+1}$ (3) IV	Δ Log Fiscal Social Spending$_{i,t+1}$ (4) IV	Party Secretary Turnover$_{i,t+1}$ (5) IV
	Panel A: Excluding Trade by Intermediary Firms				
ExpShock$_{it}$	-0.3205***	-0.1854**	-0.0193*	-0.0129**	-0.0636***
	(0.0652)	(0.0727)	(0.0094)	(0.0058)	(0.0188)
First-stage F-stat	122.4	156.1	193.7	84.60	177.5
Observations	822	802	812	760	822
R^2	0.6512	0.5137	0.7751	0.7793	0.5584
	Panel B: Destination-specific Demand Shocks				
ExpShock$_{it}$	-0.3093***	-0.1508*	-0.0180**	-0.0142*	-0.0952***
	(0.0600)	(0.0789)	(0.0072)	(0.0074)	(0.0207)
First-stage F-stat	28.75	28.46	37.86	47.85	35.40
Observations	822	802	812	760	822
R^2	0.6483	0.5183	0.7782	0.7818	0.5376
	Panel C: Gravity-based Instrument – Equation (B.5)				
ExpShock$_{it}$	-0.4145***	-0.1969*	-0.0173*	-0.0162†	-0.0750†
	(0.0675)	(0.1143)	(0.0089)	(0.0101)	(0.0480)
First-stage F-stat	51.43	63.91	90.69	69.34	104.7
Observations	822	802	812	760	822
R^2	0.6255	0.5137	0.7788	0.7803	0.5468
	Panel D: Gravity-based Instrument – Equation (B.6)				
ExpShock$_{it}$	-0.3536***	-0.1911*	-0.0214**	-0.0156*	-0.0823**
	(0.0559)	(0.0942)	(0.0088)	(0.0079)	(0.0323)
First-stage F-stat	272.1	290.3	300.1	117.6	287.3
Observations	822	802	812	760	822
R^2	0.6400	0.5145	0.7748	0.7808	0.5438
	Panel E: Growth-rate Instrument – $\kappa_i = X_{i,2012}/L_{i,2000}$				
ExpShock$_{it}$	-0.2199***	-0.1716**	-0.0177***	-0.0160***	-0.1078***
	(0.0348)	(0.0638)	(0.0042)	(0.0049)	(0.0183)
First-stage F-stat	11.32	12.32	12.16	13.07	12.79
Observations	822	802	812	760	822
R^2	0.6589	0.5167	0.7785	0.7805	0.5304
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. The alternative Bartik IVs are constructed as described in Section B.3. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table B.5: Robustness: Dropping One HS Section at a Time

Dependent variable:	**Δ CLB Events per million$_{it}$**	**Δ Log MNB "weiwen" score$_{i,t+1}$**	**Δ Log Fiscal Public Security$_{i,t+1}$**	**Δ Log Fiscal Social Spending$_{i,t+1}$**	**Party Secretary Turnover$_{i,t+1}$**
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
Range of Estimates:					
Min ExpShock$_{it}$ coef.	-0.6442***	-0.3864**	-0.0426***	-0.0292***	-0.1113**
	(0.1525)	(0.1877)	(0.0139)	(0.0112)	(0.0476)
Max ExpShock$_{it}$ coef.	-0.3086***	-0.1387***	-0.0208***	-0.0155***	-0.0711***
	(0.0530)	(0.0508)	(0.0068)	(0.0057)	(0.0189)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. For each dependent variable, the regressions drop trade flows from one HS section at a time from $ExpShock_{it}$ and the construction of the $ExpShockROW_{it}$ IV; the smallest and largest export shock coefficients with associated standard errors are reported. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.6: Effects of Future Export Shocks

Dependent variable:	**Δ CLB Events per million$_{it}$**	**Δ Log MNB "weiwen" score$_{i,t+1}$**	**Δ Log Fiscal Public Security$_{i,t+1}$**	**Δ Log Fiscal Social Spending$_{i,t+1}$**	**Party Secretary Turnover$_{i,t+1}$**
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
ExpShock$_{i,t+1}$	-0.1051	-0.0378	-0.0002	0.0031*	-0.0336
	(0.0791)	(0.0729)	(0.0034)	(0.0016)	(0.0298)
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
First-stage F-stat	24.38	24.69	24.98	26.46	22.33
Observations	822	802	812	760	822
R^2	0.6486	0.5045	0.7678	0.7681	0.5601

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All regressions are weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5, but with $ExpShock_{it}$ replaced by $ExpShock_{i,t+1}$ and instrumented with by the time-$(t+1)$ Bartik variable. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.7: Balance Test of Industry Shocks

	(1) Coef.	(2) SE
Share of college educated (%)	0.0010	(0.0027)
Manufacturing employment share (%)	0.0723	(0.0460)
Export to GDP ratio (%)	0.1892	(0.1235)
Share of population without Hukou (%)	0.0839	(0.0562)
Log GDP per capita	0.0001	(0.0005)
Log fiscal revenue per capita	0.0006	(0.0007)
Joint significance test: $\chi^2(6)$=2.77, p-value=0.8367		

Notes: This table reports coefficients from regressing product-specific weighted averages of beginning-of-period prefecture characteristics on HS6 product-level export shocks and year fixed effects. Standard errors are clustered by HS 4-digit codes. The regressions are weighted by the average HS6 product-level export exposure across prefectures. Coefficients are multiplied by 100 for readability; none of the coefficient estimates are significant at the 10% level.

Table B.8: Robustness: Alternative Clustered Standard Errors

Dependent variable:	**Δ CLB Events per million**$_{it}$	**Δ Log MNB "weiwen" score**$_{i,t+1}$	**Δ Log Fiscal Public Security**$_{i,t+1}$	**Δ Log Fiscal Social Spending**$_{i,t+1}$	**Party Secretary Turnover**$_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
ExpShock$_{it}$	-0.3207	-0.1904	-0.0214	-0.0160	-0.0742
Robust Standard Errors Clustered at:					
(i) province	(0.0539)***	(0.0725)**	(0.0069)***	(0.0059)**	(0.0192)***
(ii) export similarity	[0.0589]***	[0.0615]***	[0.0051]***	[0.0045]***	[0.0299]**
(iii) two-way clustering: (i) and (ii)	{0.0547}***	{0.0572}***	{0.0064}***	{0.0026}***	{0.0217}***
(iv) export similarity: outside prov.	⟨0.0827⟩***	⟨0.0546⟩***	⟨0.0050⟩***	⟨0.0047⟩***	⟨0.0277⟩***
(v) two-way clustering: (i) and (iv)	⟦0.0730⟧***	⟦0.0510⟧***	⟦0.0066⟧***	⟦0.0029⟧***	⟦0.0223⟧***
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y
Observations	822	802	812	760	822
R^2	0.6464	0.5146	0.7747	0.7805	0.5472

Notes: The dependent variable in Column 1 is the change in CLB-recorded events per million workers in prefecture i between year $t-1$ and t, while that in Columns 2-5 is the change in the respective political response measure between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (2) for Column 1, (8) for Columns 2-4, and (9) for Column 5. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Column 5 further includes the incumbent characteristics used as controls in Column 1 of Table 9. Robust standard errors are clustered as described in each respective row. *** p<0.01, ** p<0.05, * p<0.1.

Table B.9: Temporal Correlation between Baidu "Weiwen" Search Index and CLB Events

Dependent variable:	Δ **Log Baidu "weiwen" search index**$_{i,w}$			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Δ CLB Events per million workers$_{i,w-6}$	0.3207	0.5673**	0.3275*	0.5071**
	(0.2123)	(0.2696)	(0.1953)	(0.2409)
Δ CLB Events per million workers$_{i,w-5}$	0.7145***	0.9824***	0.6563***	0.7871**
	(0.2340)	(0.3061)	(0.2506)	(0.3367)
Δ CLB Events per million workers$_{i,w-4}$	0.7669***	1.1771***	0.6367**	0.7774**
	(0.2562)	(0.3115)	(0.2796)	(0.3662)
Δ CLB Events per million workers$_{i,w-3}$	0.6308**	0.9596***	0.5231*	0.4811
	(0.2585)	(0.3042)	(0.2949)	(0.3697)
Δ CLB Events per million workers$_{i,w-2}$	0.9440***	1.1208***	0.7206**	0.4865
	(0.2569)	(0.3351)	(0.2944)	(0.4031)
Δ CLB Events per million workers$_{i,w-1}$	0.7674***	0.9930***	0.4240	0.1984
	(0.2540)	(0.3279)	(0.2828)	(0.3724)
Δ CLB Events per million workers$_{i,w}$	0.3650	0.4586	0.0216	-0.2494
	(0.2248)	(0.3199)	(0.2534)	(0.3503)
Δ CLB Events per million workers$_{i,w+1}$	0.1573	0.2432	-0.0972	-0.2595
	(0.2002)	(0.2858)	(0.2280)	(0.3184)
Δ CLB Events per million workers$_{i,w+2}$	0.1358	0.1424	-0.0231	-0.1362
	(0.1957)	(0.2537)	(0.1953)	(0.2419)
Log Baidu "weiwen" search index$_{i,w-1}$	-0.6120***	-0.5687***	-0.9053***	-0.9132***
	(0.0260)	(0.0307)	(0.0056)	(0.0065)
Weighted?	N	Y	N	Y
Prefecture dummies?	N	N	Y	Y
Province-week dummies?	Y	Y	Y	Y
Observations	63,232	63,232	63,232	63,232
R^2	0.3840	0.3698	0.5144	0.5217

Notes: The dependent variable is the change in the prefecture log Baidu index score between week $w-1$ and w. The sample comprises all weeks in the years 2012-2015. All regressions are estimated by OLS, with six lags and two leads of the weekly change in CLB-recorded events per million workers included as right-hand side variables. All columns include province-by-week fixed effects, while Columns 3-4 further include prefecture fixed effects. Columns 2 and 4 use the prefecture working-age population from the 2010 Census as regression weights. Robust standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.10: Export Shocks and Fiscal Expenditure Shares

Dependent variable:	Δ 100 $\times$ (**Share of Fiscal measure**)$_{i,t+1}$			
Fiscal measure:	**Stability Measures**	**Public Security**	**Social Spending**	**Other Spending**
	(1)	(1a)	(1b)	(2)
	IV	IV	IV	IV
ExpShock_{it}	-0.1500*	-0.0677**	-0.0878	0.1500*
	(0.0845)	(0.0266)	(0.0757)	(0.0845)
100$\times$Share Fiscal Measure_{it}	-0.8772***	-0.8745***	-0.8735***	-0.8772***
	(0.0478)	(0.0655)	(0.0453)	(0.0478)
Additional time-t controls?	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y
First-stage F-stat	127.8	109.5	126.3	127.8
Observations	755	812	760	755
R^2	0.7815	0.8094	0.7633	0.7815

Notes: The dependent variable is the change in the share of fiscal expenditure under the respective column headings in prefecture i between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (8). The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.

Table B.11: Export Shocks and Prefecture Fiscal Expenditure by Social Spending Categories

Dependent variable:	Δ **Log Fiscal measure**$_{i,t+1}$				
Fiscal measure:	**Public Services**	**Education**	**Social Security**	**Medical Services**	**Public Housing**
	(1)	(2)	(3)	(4)	(5)
	IV	IV	IV	IV	IV
	Panel A: Average Effects				
ExpShock$_{it}$	-0.0087*	-0.0121***	0.0058	-0.0076*	-0.0524**
	(0.0046)	(0.0034)	(0.0083)	(0.0039)	(0.0238)
Log Fiscal Measure$_{it}$	-0.9770***	-0.8676***	-1.0897***	-0.9575***	-1.1611***
	(0.0546)	(0.0671)	(0.1004)	(0.0620)	(0.1170)
First-stage F-stat	104.8	166.5	76.06	118.8	160.1
Observations	814	817	816	817	764
R^2	0.7606	0.8088	0.6791	0.7847	0.7403
	Panel B: Heterogeneous Effects				
ExpShock$_{it}$	0.0338	0.0452***	0.1015	-0.0761***	0.2498**
	(0.0308)	(0.0147)	(0.0600)	(0.0198)	(0.0986)
Δ(Events/L)$_{it}$×ExpShock$_{it}$	-0.0132***	-0.0041	-0.0048	0.0045	-0.0817***
	(0.0045)	(0.0033)	(0.0081)	(0.0030)	(0.0099)
(FiscalRev/L)$_{i,2012}$×ExpShock$_{it}$	-0.0120	-0.0318***	-0.0544	0.0405***	-0.1007
	(0.0192)	(0.0092)	(0.0447)	(0.0103)	(0.0682)
(49≤Age≤53)$_{it}$×ExpShock$_{it}$	-0.0100	-0.0165	-0.0314	0.0029	-0.0506
	(0.0170)	(0.0101)	(0.0202)	(0.0139)	(0.0649)
Δ(Events/L)$_{it}$	-0.0037	0.0012	0.0129**	0.0029	-0.0150
	(0.0038)	(0.0033)	(0.0058)	(0.0044)	(0.0148)
(49≤Age≤53)$_{it}$	-0.0119	-0.0099	0.0019	-0.0077	-0.0441
	(0.0118)	(0.0097)	(0.0126)	(0.0149)	(0.0289)
Log Fiscal Measure$_{it}$	-0.9861***	-0.8713***	-1.0548***	-0.9964***	-1.1692***
	(0.0610)	(0.0695)	(0.0886)	(0.0668)	(0.1144)
First-stage F-stat	18.55	22.80	20.28	21.50	17.31
Observations	814	817	816	817	764
R^2	0.7582	0.8139	0.6744	0.7710	0.7354
Additional time-t controls?	Y	Y	Y	Y	Y
Prefecture dummies?	Y	Y	Y	Y	Y
Province-year dummies?	Y	Y	Y	Y	Y

Notes: The dependent variable is the change in log fiscal expenditure by social spending categories under the respective column headings in prefecture i between year t and $t+1$ (i.e., one year after the export shock). All columns report IV regressions, weighted by the prefecture's working-age population in 2010, based on the specification in (8). Panel A reports the average effects of the export shock on the respective fiscal spending measures. Panel B explores heterogeneous effects: The $\Delta(\text{Events}/L)_{it}$ variable is the change in CLB-recorded events per million between year $t-1$ and t. $(\text{FiscalRev}/L)_{i,2012}$ is the initial local fiscal revenue per worker in 2012. $(49\leq\text{Age}\leq53)_{it}$ is a dummy variable for whether the prefecture party secretary is between ages 49 and 53 (inclusive) in year t. The additional time-t controls are those used in Column 3 of Table 2, namely: the changes in the log college-enrolled, mobile-use, and internet-use shares. Robust standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.