Firm Response to Competitive Shocks: Evidence from China's Minimum Wage Policy

Harald Hau

University of Geneva, CEPR, and Swiss Finance Institute*

Yi Huang

Graduate Institute, Geneva, and CEPR**

Gewei Wang

Peking University***

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Abstract

The large regional variation in minimum wage levels during the period 2002-08 in China implies that Chinese manufacturing firms experienced competitive shocks as a function of firm location and their low-wage employment share. We find that minimum wage hikes accelerate the input substitution from labor to capital, reduce employment growth and accelerate total factor productivity growth—particularly among the less productive firms under private Chinese or foreign ownership, but not among state-owned enterprises. The heterogeneous firm response to labor cost shocks can be explained by differences in management practices, and suggests that management quality and competitive pressure are complementary.

JEL Classification: D24, G31, J24, J31, O14
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*University of Geneva, GSEM, Geneva Finance Research Institute, 42 Bd du Pont d'Arve, 1211 Genève 4, Switzerland. Tel.: (++41) 22 379 9581. E-mail: prof@haraldhau.com. Web page: http://www.haraldhau.com.

**Graduate Institute of International and Development Studies, Maison de la paix, Chemin Eugène-Rigot 2, 1202 Genève, Switzerland. E-mail: yi.huang@graduateinstitute.ch.

***E-mail: geweiwang@gmail.com.

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Data Sharing and Replication

For easy replication of the results, we provide here a dropbox link to (i) the Chinese firm data file (.dta file), (ii) the data of minimum wage growth in China (.dta file), and (iii) the STATA program generating the main tables (.do file) at the following link:

http://www.haraldhau.com/can-higher-minimum-wages-accelerate-productivity-growth/#tab-id-2

1 Introduction

This paper explores the endogenous productivity response of Chinese firms exposed to minimum wage shocks. During the period 2002–08, China's 2,867 counties and 333 cities implemented more than 17,000 changes in the local minimum wage, of which more than a quarter was larger than 20% as shown in Figure 1. Many of the most affected firms are in the manufacturing sector and produce tradeable products. Hence, any large local minimum wage increase represents an important competitive shock to firms if their competitors in other locations or with a different wage structure do not face the same increase in labor costs. Firms experiencing a substantial labor cost increase should *ceteris paribus* substitute capital for labor, reduce output and consequently lose market share. Yet a more precarious competitive position can simultaneously facilitate firm restructuring in pursuit of higher productivity, which leads to the question – Did adverse cost shocks accelerate the productivity growth of Chinese manufacturing firms? And did other factors like firm ownership and management quality influence the endogenous firm response?

A "Darwinian" view of competition regards adverse cost shocks as an opportunity to restructure and reduce organizational slack. Substantial reorganization often requires a consensus among managers and the workforce, and may be easier to reach under increased external pressure.[1] Accordingly, a theoretical management literature argues that increased competitive pressure reduces agency problems and can even substitute for performance contingent managerial pay incentives (Schmidt, 1997; Aghion, Dewatripont and Rey, 1999). By this Darwinian perspective, adverse competitive shocks can raise productivity because they align interests irrespective of the quality of management. Management practice is simply the optimal firm adjustment to its environment. The largest benefits from competitive shocks may accrue to the firms with the worst ex ante agency problems if stronger external market/survival incentives can substitute for internal incentive practices.

An alternative "managerial" view emphasizes the importance of management quality for firm productivity, whereby firms are endowed with different management technologies. In a series of papers, Bloom *et al.* (2010), Bloom *et al.* (2016b), Bloom and van Reenen (2007, 2010), and van Reenen (2011) have documented the positive correlation between firm productivity

[1] This view has been popularized by Michael Porter (1990).

and the quality of management practices within industries and across countries. Bloom *et al.* (2017) combine six data sets on management practices to show that better managed firms export more, produce better products with higher prices and source their inputs more widely. Micro data on German firm employees suggest that management quality and the pay premia among the highest paid employees account for productivity differences across firms (Bender *et al.* 2016). Such a positive correlation could be the result of better managed firms responding more effectively to competitive challenges, so that competitive shocks and management quality are complementary in their effects on productivity growth. Yet, there is surprisingly little direct evidence as to whether management quality indeed plays a *causal* role in the evolution of firm productivity.

As in most emerging markets, Chinese firms feature large heterogeneity in firm productivity, management practice, firm governance and corporate ownership. The coexistence of state-owned enterprises (SOEs), private-owned (Chinese) firms, and foreign-owned firms supports this variation with considerably higher levels of management quality (and pay) observed in foreign owned firms, as illustrated in Figure 2. Adjusted for firm size, industry fixed effects and sampling year fixed effects, total management practice measured in the three dimensions of (1) monitoring practices (the collection and processing of production information); (2) target-setting practices (the ability to set coherent, binding short- and long-term targets); and (3) incentive practices (merit-based pay, promotion, hiring, and firing) is considerably lower in SOEs and highest in foreign-owned firms.[2] Labor cost shocks caused by local minimum wage changes can function as a treatment effect to explore if and how different ownership types and management practices shape the endogenous productivity response within China's vast manufacturing sector.

Our analysis draws on both intertemporal and geographical (county-level) variation of Chinese minimum wages for the period 2002–08. In addition, we take account of the heterogeneous exposure of firms to minimum wage shocks in a two-step procedure. First, we estimate the impact of increases in the minimum wage on a firm's average wage increase. Here we assume that firm exposure is a non-linear function of the distance of the average firm wage from the prior local minimum wage—proxying for the "utilization" of low-wage labor. Second, the reduced

[2] The survey data on Chinese firms is based on Bloom and van Reenen (2010). As the management scores have no cardinal meaning, it is sensible to express them relative to their standard deviation. We therefore report z-scores for each measure by dividing the conditional management scores by the conditional standard deviation.

form regressions capture "treatment heterogeneity" by interacting the estimated firm-specific exposure with the observed local minimum wage increase. In addition, we allow the more exposed low-wage firms to differ from their industry peers with higher wages: we use firm fixed effects to account for any time-invariant omitted variables that could influence the firm-specific growth trend of any dependent variable. Our identification of the endogenous productivity response assumes that the "timing of the productivity surge" for each minimum wage exposed firm occurs in the year when the new local minimum wage increase becomes effective. We also add interacted industry-year fixed effects to control for any industry wide productivity dynamics.

Our main empirical findings are threefold. First, in accordance with neoclassical firm theory, we find that, relative to their high-wage industry peers, low-wage firms accelerate their labor to capital substitution in the year of the local minimum wage increase. The effect on employment growth is clearly negative across firm types and extends to state-owned enterprises (SOEs). Yet large and foreign-owned firms with a low average wage show the largest labor substitution effect in their response to the labor cost shock.

Second, adverse labor cost shocks due to increased minimum wages do not reduce relative output or capital input as predicted by neoclassical firm theory under constant productivity growth. The non-negative relative output growth reflects a relative increase in total factor productivity (TFP) for low-wage firms in the year of the minimum wage increase. The endogenous productivity response of low-wage firms to adverse labor cost shocks is robust to different (revenue) TFP measures based on cost share methods or proxy methods (Levinsohn and Petrin 2003; Ackerberg *et al.* 2015). Moreover, the finding of accelerated TFP growth is more pronounced in the bottom than in the top half of the intra-industry TFP distribution. Low-TFP firms therefore feature some productivity "catch-up" under minimum wage shocks.

Third, we find large heterogeneity in the endogenous productivity response by firm type: Foreign-owned firms (or firm with a substantial foreign ownership share) show the largest increase in TFP in the year of the minimum wage increase followed by Chinese private-owned firms, whereas no endogenous productivity surge is observed for state-owned enterprises (SOEs). The ownership dependent endogenous productivity response is the main finding of our paper.

Our final contribution is of a more exploratory nature and seeks a coherent interpretation of the ownership dependent productivity response. The Darwinian perspective that increased competitive pressure represents a general remedy against managerial slack cannot account for non-responsive SOEs unless their employees are better protected under financial distress. But this generally does not seem to be the case in China where massive worker layoff in SOEs are documented (Hsieh and Song, 2015). Similarly, efficiency wage theory is at odds with this finding because bottom-up incentive effects should not be conditional on firm ownership. Instead, variations in management practice appear to matter most. We extrapolate survey data about management practice in Chinese firms (Bloom, Mahajan, McKenzie and Roberts, 2010; Bloom and van Reenen, 2007, 2010) to the full firm sample and find that superior management practices, particularly in foreign-owned firms, can account for the heterogeneous productivity response to adverse labor cost shocks. Management quality and competitive pressures appear to feature a complementary relationship in the pursuit of productivity growth.

We subject these results to a variety of robustness tests. Our TFP measures are based on deflated firm revenues using industry-specific output deflators which may not reflect a firm's true output prices. This becomes a particular concern if higher minimum wages are passed through to higher product prices. To address this issue, we complement the TFP measures with independently collected export statistics from the Chinese customs authorities which report firm specific export quantities and prices separately. The customs data reveal that minimum wage shocks translate (again for private and foreign-owned firms only) into larger export quantities, but not into higher export prices. Therefore, we argue that TFP mismeasurement due to incorrect product price deflators is unlikely to account for the evidence. Specifically, we can exclude that output price mismeasurement accounts for the strong TFP surge observed for exporting firms under minimum wage shocks. While more monopolistic (non-export) sectors in which SOEs operate could allow for more pass-through, we do not observe any (price-induced) output increase or (mismeasured) TFP increase for SOEs in the year of the minimum wage increase as should be expected under the pass-through hypothesis. We also note that the largest TFP increase is concentrated in firms of low initial TFP and partially accounted for by significant employment reductions, which we observe directly without price distortions.

A second concern relates to survivorship bias. Particularly for small firms, our sample is unbalanced and the sampling may ignore less productive firms exiting the market. Firm exit could imply higher output and potentially higher TFP for surviving firms if the latter operate at undercapacity or at an inefficient scale. But for such firm exit to influence our estimates, it has to be clustered in the year and location of the minimum wage increase and the demand shift from the exiting firm has to be biased towards low wage firms. While we find it implausible that firm exit predominantly profits low wage firms, there is also no evidence that reporting discontinuities—proxying for firm exit—coincide with local minimum wage increases in any economically significant manner.

We also explore if local minimum wage changes respond to anticipated productivity gains of local firms. While local government may adjust the minimum wage policy to aggregate local economic conditions, it seems unlikely that they would do in anticipation of a *relative* productivity growth difference between private/foreign firms and SOEs. This latter policy behavior is required to explain the difference in correlation by ownership type, assuming that reverse causality accounts for the evidence. Additional regressions reported in Table A4 of Internet Appendix indeed show no evidence that performance differences between SOEs and other firms matter for the minimum wage setting.[3] Local authorities may also lack information on foreign firm productivity, and could at best respond to the stock market valuations of local listed companies. However, stock market valuations of listed local companies (under private or foreign ownership) again do not predict minimum wage changes.[4]

2 Related Literature

The role of competition remains a key topic in the research agenda on the determinants of growth (Syverson, 2011). Unfortunately, the level of competition is often inextricably entangled with the level of technological progress itself so that competitive shocks are rarely exogenous to productivity growth. The minimum wage shocks to the Chinese manufacturing sector represent a source of competitive pressure which is regulatory in nature, precisely identified in terms of geographic scope, and in their exact timing are largely exogenous to the firm-specific productivity process.

A variety of other competitive shocks have been studies in the previous literature. Trade agreements represent a different regulatory shock which can exogenously intensify competition

[3]Political economy considerations suggest that local authorities could be more sensitive to the performance of SOEs so that the reverse causality channel is more plausible for SOEs. Yet precisely for SOEs we find no correlation between TFP growth and the minimum wage increases.

[4]Note also that foreign firms account for no more than 28% of manufacturing employment over the period 2002–08.

and has therefore attracted considerable research interest. Bernard, Jensen and Schott (2006) study the response of U.S. manufacturing industries and plants and show that declining trade barriers tend to accelerated productivity growth. Lileeva and Trefler (2010) look at the response of Canadian plants to U.S. tariff cuts and finds a positive productivity and innovation effect of improved market access.[5] Various studies document that lower input tariffs lead to higher firm productivity, for example in China (Brandt et *al.* 2017), India (Topalova and Khandelwal 2011), and Indonesia (Amiti and Koning 2007). But revenue-based productivity inference on tariff changes is difficult as tariffs generally feature no firm variation within an industry and simultaneously change the entire structure of input and output prices. Giroud and Müller (2010, 2011) examine geographic variations in the threat of market entry due to business combination laws and show that more competition mitigates managerial slack and supports higher operating performance. Khanna and Tice (2000) study the heterogeneous response by discount department stores faced with Wal-Mart's market entry. Duggan (2000) studies the effect of changing government subsidies for hospital admission and finds that both private for-profit and private not-for-profit hospitals respond more strongly to changing financial incentives than public-owned hospitals. Schmitz (2005) documents a large productivity increase by iron ore mines of the Great Lakes region after 1985 in response to a new competitive threat from cheaper oversea producers.

An important policy debate centers on the response of U.S. and European firms to China's integration into the global supply chain. Bena and Simintzi (2016) find that access to cheap labor following the 1999 U.S.-China trade agreement lowers U.S. firm investment in (labor substituting) process innovation and reduces the corresponding patent production. Similar negative effects on U.S. firm investment and patenting are reported by Autor *et al.* (2016), whereas Bloom, Draca and van Reenen (2016) find that firms across 12 European countries innovated more when facing intensifying product market competition. Our paper is concerned with labor cost shocks within China's vast manufacturing sector. Unlike the slow import penetration process affecting non-Chinese firms, the direct labor cost shocks originating in Chinese minimum wage regulation can be dated very precisely and our analysis focuses on the firm adjustment at the time the minimum wage hike becomes effective.

[5] For a discussion of financial firm performance after tariff changes see also Boven III, Frésard. and Taillard (2015) and Frésard and Valta (2016).

Our most important result concerns the endogenous productivity response to higher minimum wages by firms facing higher labor costs. We highlight that this productivity acceleration is stronger for low initial levels of productivity and contingent on firm ownership. This rules out certain transmission channels, like efficiency wages, as the source of the productivity gain. If higher wages simply improve the quality of labor supply (i.e. the non-contractable effort level) or reduce labor turnover, we expect to find more uniform productivity gains across firms of any ownership type. Our evidence points instead to the role of firm ownership and in particular, management practice (Bloom and Van Reenen, 2010) as the explanation for differences in firm adaptability. It also points to a general weakness of the state-owned sector to cope with productivity challenges (Song, Storesletten and Zilibotti, 2011; Zhu, Brandt and Tombe, 2013; Song and Wu, 2015; Hsieh and Song, 2015).

Labor economics mostly focuses on the direct employment effect of minimum wage changes. Recent studies including Brown (1999), Meer and West (2013), and Dube, Lester, and Reich (2015) do not arrive at any clear consensus on the employment effect. Firm-level evidence by Katz and Krueger (1992), Card and Krueger (1994), and Neumark and Wascher (2008) shows negligible or positive employment responses in U.S. data.[6] By contrast, the considerably higher minimum wage variation in the Chinese manufacturing sector, combined with a higher share of low wage workers, creates a more propitious setting for negative employment effects. Wang and Gunderson (2012), Fang and Lin (2013), Jia (2014), and Huang, Loungani, and Wang (2014) all find negative employment effects for at least parts of the Chinese labor force. We contribute to the existing evidence based on improved identification techniques that account for the heterogeneous exposure of Chinese manufacturing firms to minimum wage increases.

Macroeconomic research has highlighted the role of productivity dispersion for a country's aggregate productivity. Emerging countries in particular feature large productivity gaps between their most and least efficient firms (Hsieh and Klenow, 2009, 2014; Bloom, *et al.*, 2010; Foster, Haltiwanger, and Krizan, 2010; Syverson, 2011) which may pull down overall aggregate industry productivity. Minimum wage policies in China appear to have lowered such productivity dispersion at least among private-owned firms. Related work by Haepp and Lin (2015) also

[6]We note that endogenous productivity effects could make the employment response of minimum wage increases industry-specific: A productivity effect can potentially dominate any input factor (labor) substitution effect whenever the scope for factor substitution in a given industry is limited—thus accounting for some of the ambiguous or insignificant employment effects found in the literature.

finds positive capital investment effects in private firms following a minimum wage increase; however they do not examine overall firm productivity.

Understanding the determinants of productivity growth has significance beyond emerging markets: Developed countries have been characterized by decreasing labor productivity growth over the last decades, with wages at the low end of the pay scale experiencing hardly any real wage increases. While the orthodox view considers labor productivity as the cause of real wage growth, evidence on the endogeneity of firm productivity to labor costs suggests that the reverse causality could also be an important channel (Pessoa and Van Reenen, 2013). An abundant supply of low-wage labor could retard the adoption of new capital–intensive technologies and contribute to a productivity slowdown (Bena and Simintzi, 2016). Historical research on the English industrial revolution has highlighted labor scarcity and high wages as a driver of innovation and productivity growth (Allen, 2009; Economist, 2018).

Finally, we can relate our evidence to discussions on international competitiveness. An appreciating currency is sometimes portrayed as forcing domestic firms to continuously increase firm productivity (Porter, 1990; Boltho, 1998). However the evidence for such a currency channel remains elusive because of plausible reverse causality from increased productivity to an appreciating currency, known as the Harrod-Balassa-Samuelson effect.[7] By contrast, the labor cost shocks in our study originate in more exogenous policy measures and therefore allow for a better causal inference on the same economic mechanism between an adverse competitive shock and the productivity response of the firm.

3 Theoretical Considerations

Average firm wages vary across firms within the same industry and this partially reflects differences in average labor quality. In a competitive labor market, higher individual labor productivity translates into a higher wage. This allows for the coexistence of firms with low-skill and high-skill labor, where the high-skill firm employs fewer workers at a higher average wage. But such firm differences in the wage structure imply that a minimum wage increase has heterogeneous effects on the labor costs of individual firms, even if they are subject to the same

[7] Plausible exceptions to this argument are unexpected changes in the exchange rate regime, like the appreciation of the Swiss franc on January 15, 2015. For evidence on this event see Efing *et al.* (2016).

regulatory change. In Appendix A, we provide a simple neoclassical model in which a low-wage and a high-wage firm compete.

For a minimum wage increase $\Delta \ln w^{\min}$, we assume that the induced average wage increase $\Delta \ln w_s$ for firm s depends on how close the average firm wage w_s is to the previous minimum wage $w^{\min}$; the smaller the ratio $w_s/w^{\min}$ — the larger the average wage increase. To capture this non-linear relationship between the average firm wage increase and a minimum wage hike, we can define an *impact function* (IF) as follows

$$IF(w_s/w^{\min}) = \frac{\Delta \ln w_s}{\Delta \ln w^{\min}} \quad \text{with} \quad IF' < 0. \tag{1}$$

In the empirical part, we estimate the impact function using the functional form $IF(w_s/w^{\min}) = \lambda \left(w_s/w^{\min}\right)^{-(k+1)}$, where the parameter $\lambda > 0$ determines the strength of the average wage effect and $k > 0$ governs its convexity. Correctly characterizing the impact function allows for a better identification of the effective firm exposure to any given minimum wage increase.

Under labor market rigidities, firms cannot easily replace all low-wage low-skill labor with high-wage high-skill labor, but they can still increase the capital intensity of their production to reduce labor costs. It is straightforward to show that for a neoclassical Cobb-Douglas production function, a labor cost shock $IF_s \Delta \ln w^{\min}$ for firm s implies a proportional change in the log ratio of capital and labor $\Delta \ln(K_s/N_s)$, where K_s denotes the capital stock and N_s the number of employees. This implication can be directly tested for the Chinese panel of manufacturing firms. Additional theoretical implications concern a firm's competitive position after the minimum wage shock $\Delta \ln w^{\min}$. The larger the effective labor cost shock $IF_s \Delta \ln w^{\min}$, the larger its predicted *reduction* in (value added) output $\Delta \ln Y_s$, in the capital stock $\Delta \ln K_L$, in employment $\Delta \ln N_L$, and firm profits $\Delta \ln \Pi_s$ relative to industry peers. Moreover, the more competitive the industry, the larger the relative output loss, factor input reduction, and profit decrease.

Yet these implications are subject to the *ceteris paribus* condition that firm do not endogenously react with an increase in productivity. An endogenous productivity increase implies that the firm's output and inputs decrease less or even increase.[8] We can measure the productivity effect directly by constructing TFP measures and relating them to the labor cost shock

[8] The reader is referred to the Internet Appendix A for a more detailed exposition.

$IF_s \Delta \ln w^{\min}$.

3.1 Endogenous Productivity Response and its Channels

We distinguish two theories that can rationalize a differential productivity effect under adverse competitive shocks. First, the *theory of efficiency wages* assumes that high wages can increase labor productivity because higher pay can mobilize a higher level of labor productivity in a way that the labor contract itself cannot. Higher wages increase any potential employee loss related to contract termination and as a consequence, the opportunity cost of shirking increases. It might also reduce the cost of labor turnover which tends to be high among low skill manufacturing workers. Positive productivity effects of minimum wage increases rely on an inefficiently low prior wage and represent an improvement in labor productivity at the bottom of the organizational hierarchy. Importantly, such productivity gains should be available independently of a firm's governance, and should not be contingent on firm ownership.

Second, an endogenous response could result from *managerial incentives* if private payoffs of managers are a concave function of relative changes in firm profitability. Performance monitoring mechanisms can benchmark the firm's performance against that of the competitor and sanction relative underperformance, for example, with an increased likelihood of firing the CEO or the top management team. Such a monitoring and incentive mechanism can also rationalize an endogenous productivity response proportional to the size of the competitive shock.

3.2 Firm Differences in the Endogenous Response

Firm heterogeneity in the endogenous response to competitive shocks provides valuable insights into the underlying economic mechanism. Efficiency wage theory locates the productivity gain in the individual worker's increased desire for employment retention and therefore implies a similar productivity gain across firm types with the same share of minimum wage labor. A variant of the efficiency wage model argues that work effort increases after a wage increases because employees reciprocate the "kindness" of the employer, but it is less clear if such reciprocation extends to regulatory wage increases of our analysis. Furthermore, for workers who earn higher wages, the difference between their wage and the "reference wage" of the lowest paid worker is reduced so that they may exert less effort (Falk, Fehr, and Zehnder; 2005). Again, this theory does not predict substantial asymmetry in the firms' productivity response.

Both the "Darwinian" perspective and "managerial" view of firm productivity share the idea that large and persistent x-inefficiency exists in many industries. The Darwinian perspective emphasizes the firm's survival threat as a bound on x-inefficiency and can account for a heterogeneous productivity response to the extent that employees in SOEs and private firms differ in their respective unemployment risks under financial distress. But the Chinese experience does not provide much support for a privileged treatment of ordinary SOE employees in the period 1998-2007, when approximately 80% of SOEs either terminated their activity or were restructured into private-owned companies (Hsieh and Song, 2015). The massive layoffs in SOEs are referred to as the "breaking of the iron rice bowl" and concern the dismissal of roughly 39 million SOE employees in the period 1997-2004 (Cai, Park, and Zhao; 2008, page 177, Table 6.2). Most medium-sized and small-sized SOEs seem to have faced survival challenges under financial distress similar to their private-owned competitors, which makes any difference in their endogenous response more puzzling.[9] Lastly, the Darwinian perspective does not predict any difference in the productivity response between private-owned Chinese and foreign-owned firms.

The "managerial" view focuses on firm capacity for implementing a higher productivity level. Work by Bloom and Reenen (2007, 2010) has emphasized the role of management practice for firm productivity and related large TFP differences between firms from developed and developing countries to the quality of firm management. As illustrated in Figure 2, differences in management quality are particularly pronounced between foreign-owned firm and SOEs, where foreign-owned firms score higher on monitoring, target-setting and incentive practices. As shown in the Web Appendix to this paper, performance incentives relative to industry peers can trigger a strong endogenous productivity response of low wage firms under adverse labor cost shocks. But while relative performance targeting and monitoring could be an effective management tool, such management practices appear to enjoy unequal implementation (Figure 2) so that the endogenous response to cost shocks becomes heterogeneous and dependent on management quality. The observed patterns of endogenous productivity response to minimum wage shocks support the "managerial" view of the firm.

[9] Only politically connected top managers arguably enjoyed a relatively higher employment security compared to private sector employees.

4 Data

4.1 Minimum Wage Policy in China

China's minimum wage policy dates back to July 1994, when a new labor law stipulated a system of minimum wages. According to Article 48 of the then labor law, firms in the formal sector were required to comply with the minimum wage set at the local level. Provincial governments were authorized to set the local minimum wage, which could vary across cities and even counties within the same province. City-level and county-level authorities could negotiate local minimum wages with their respective provincial authorities (Casale and Zhu, 2013). Local governments therefore obtained substantial influence over the particular minimum wage policy applicable in their city or county; higher authorities would mostly review these policies and take responsibility for their enforcement. Enforcement of minimum wage policies was improved over time. After 2003, the frequency of minimum wage changes increased in a period of rapid industrial growth.

In March 2004, the Ministry of Labor and Social Security initiated a policy reform to achieve a more uniform implementation of minimum wage policies. The reform measures emphasized (1) an explicit extension of coverage to town/village enterprises and self-employed businesses; (2) a new standard for hourly minimum wages; (3) an increase in penalty for non-compliant enterprises from 20-100% to 100-500% of the wage shortfall; and (4) more frequent minimum-wage adjustment (at least once every two years). Moreover, local departments of labor had to exercise supervision within the scope of each hierarchical administration and evidence suggests that compliance with minimum wage standards became much more uniform (Su and Wang, 2014). Anecdotal evidence further suggests the announcement of minimum wage increases precede their implementation only by a few months.[10]

The minimum wage data used in this paper comes from the Ministry of Human Resources and Social Security (MOHRSS) and the China Academy of Labor and Social Security; it covers the period 1996-2012. To match minimum wage data to the annual reporting frequency of the firm data, we calculate (average) annual minimum wages for each county/city whenever minimum wage adjustments occur during the calendar year. The distribution of (annual)

[10] This implies that anticipation effect in the year prior to the implementation are unlikely to pose a problem for our study.

minimum wage changes is depicted in Figure 1.

For much of the analysis, we only use data for the period 2000-08, because reliable firm level survey data starts only in 2000 and stops in 2008. The Chinese statistical authorities discontinued the release of data from the Annual Survey of Industrial Firms (ASIF) in 2009. Table 1, Panel A reports summary statistics on (nominal) minimum wage changes expressed in log changes $\Delta \ln w_t^{\min} = \ln w_t^{\min} - \ln w_{t-1}^{\min}$. The average annual increase in the minimum wage is high at 11.3% per year with an extremely large (cross-sectional) standard deviation of approximately 10% in every sample year from 2002 to 2008. China is exceptional in both the magnitude of minimum wage changes and its enormous regional heterogeneity.

Generally, minimum wage changes occurred less frequently before 2003, but became more frequent thereafter. Huang, Loungani, and Wang (2014) explore the determinants of minimum wage change and find very little evidence that economic conditions, like local growth or unemployment, have explanatory value in predicting minimum wage changes.[11] Table A4 of the Internet Appendix provides additional analysis that local business cycle variables do not predict local minimum wage changes. We therefore argue that the *timing* of the minimum wage change is determined by internal party politics, which represents an exogenous factor for the purpose of this study.

4.2 Chinese Firm Data

The firm-level data in our study comes from the Annual Survey of Industrial Firms (ASIF), also known as the Chinese Industrial Enterprise Database (CIED). According to this survey, "large-scale" industrial firms file detailed reports every year to their local Bureau of Statistics. The National Bureau of Statistics (NBS) then aggregates the data to produce key statistics for industrial output and employment and publishes them in the China Statistical Yearbook. Our sample spans the period 2002–08 and except for the year 2008, it contains the same number of observations used by NBS. The firm sampling covers the full sample of large firms (those with more than 1,000 employees) and a large proportion of medium firms (between 200 and 1,000 employees), whereas coverage is more incomplete for small firms with fewer than 200 employees. The survey covers all industrial sectors and the mining sector and accounts for roughly 88%

[11] The level of the minimum wage is more strongly correlated with the local price levels, however our analysis considers firm adjustment to largely unpredictable minimum wage changes.

of the national industrial output. In 2009, public access to the ASIF was discontinued for one year, so there are no reliable firm survey data available for that year. No official reason was provided, but speculations circulated that the statistical authorities tried to obstruct any investor inference about a recession in the Chinese manufacturing sector.

Reporting errors in the survey requires a stringent filtering process for data errors. The various filters employed are documented in the Internet Appendix. We filter out firm observations with abnormal growth rates of real minimum wages and exclude firm observations for which critical firm variables are in the 1% upper and lower tail of the yearly distribution. Table 1, Panel B provides the summary statistics of the full firm sample, which (after the filtering procedure) contains 1,201,803 firm-year observations. A breakdown of the sample by ownership type yields 113,291 firm-years observations for state-owned enterprises (SOEs), 829,110 observations for private-owned firms (in Chinese ownership) and 259,402 firm years for foreign-owned firms. Following Hsieh and Song (2015), our ownership designation is based on control rights by the dominant shareholder rather than legal incorporation. This avoids incorrect categorizations of firms which have a state entity as their dominant shareholders, but which are nevertheless incorporated legally as limited-liability corporations or share-holding firms. Changes in ownership designation are relatively rare and occur in only 2.6% of all firm-year observations.

The summary statistics reported in Table 1 concern the (log) annual change in the capital to labor ratio $\Delta \ln(K/N)$, the (log) annual change in value added output $\Delta \ln Y$, the (log) employment change $\Delta \ln N$, the log change in the capital stock $\Delta \ln K$, and two measures of total factor productivity growth denoted $\Delta \ln(A1)$ and $\Delta \ln(A2)$, respectively. Value added output, capital, and productivity are measured in real terms and deflated by the appropriate industry or intermediate input price indices.

Average (value added) output, capital, and labor growth differ by firm size. The largest output growth is found for private-owned firms with an average annual (log) growth of 18.6%, followed by foreign owned firms at 14.8% and SOEs with only 8.0%. Similarly, annual productivity growth is largest for privately owned firms (at 10.7% and 11.1%, for $\Delta \ln(A1)$ and $\Delta \ln(A2)$, respectively), followed by foreign owned firms (at 9.2% and 9.3%) and SOEs (at 7.7% and 7.8%). Correspondingly, the capital intensity, as measured by the (log) capital to labor ratio $\ln(K/N)$, grows faster for private-owned firms at 10.6% compared with only 5.4% and

5.2% for foreign owned firm and SOEs, respectively.[12]

One shortcoming of the Annual Survey of Industrial Firms (ASIF) is a lack of firm-specific output price deflators. As a consequence, we can only impute production output and TFP growth based on the industry output deflators. Heterogeneous firm exposure to minimum wage shocks in combination with wage pass-through to product prices may raise concerns that the industry price deflator could underestimate firm-specific price inflation and arrive at overestimated output and TFP changes precisely for those firms that experience the largest minimum wage increases. To explore this measurement bias, we use Chinese customs data that report value-based and quantity-based measures for exporting firms separately. The change in the (log) value of exported output ($\Delta \ln Exp\_Value$) can be decomposed into a (log) volume change ($\Delta \ln Exp\_Volume$) and a change in log prices ($\Delta \ln Exp\_Price$) at the firm level for exported output with summary statistics provided in Table 1, Panel C. The average nominal annual export growth was 30.9% in volume terms and 24.0% in value terms for the period 2002-08. For exporting firms, we show in Section 7 that minimum wage shocks do not affect firm-specific product prices, which reassures us about the quality of our TFP measures. In the analysis, we report separately the endogenous TFP response of exporting firms, which is as strong as for foreign-owned firms.

5 Identification of Minimum Wage Exposure

A minimum wage increase should primarily affect firms with numerous employees at or near the current minimum wage. Unfortunately, data for the entire distribution of employee wages at the firm level are not available for Chinese firms. Instead, we use the average firm wage w_s as a proxy for the percentage of employees likely to be affected by a minimum wage increase. In particular, we assume that the ratio $w^{\min}/w_s$ of the local minimum wage and the firm's average wage (both measured in year $t-1$) determines the impact of any minimum wage increase on average firm wages. The corresponding (non-linear) relationship can be estimated directly using the firm data. Formally, we capture the elasticity of average firm wages to minimum wage changes by the convex (impact) function $IF_s(k+1) = \lambda(w_s/w^{\min})^{-(k+1)}$, where the parameter k governs the convexity of the function.

[12] Detailed summary statistics by firm ownership are reported in Table A2 in the Web Appendix to this paper.

In order to estimate the convexity parameter k as precisely as possible, it is helpful to estimate k for *level changes* in the minimum wage $\Delta w^{\min}$ and firm wages Δw_s rather than *log changes*. This reduces the convexity of the impact function by one unit from $k+1$ to k, because

$$\frac{d\ln w_s}{d\ln w^{\min}} = \frac{w^{\min}}{w_s}\frac{dw_s}{dw^{\min}} = \frac{w^{\min}}{w_s} IF_s(k) = IF_s(k+1). \qquad (2)$$

To obtain the implied impact function for log changes, we simply increase the level estimate $\widehat{k}$ to the corresponding changes $\widehat{k}+1$ for the impact function in log terms.

Next, we decompose the annual (log) firm wage change $\Delta \ln w_s$ into three terms: (1) the interaction term $IF_s \times \Delta \ln w^{\min}$ between the impact factor and the minimum wage change characterizing the relatively higher average wage change for low wage firms; (2) the trend growth proportional to the impact factor IF_s for all low wage firms; and finally (3) the general wage inflation proportional to the minimum wage change $\Delta \ln w^{\min}$ affecting all firms equally. Formally, the panel specification becomes

$$\Delta \ln w_s = \beta \, \left[IF_s \times \Delta \ln w^{\min}\right] + \gamma \; IF_s + \delta \; \Delta \ln w^{\min} + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}, \qquad (3)$$

where $\mu_{Ind \times Year}$ denotes interacted industry and time effects and ν_s a firm fixed effect.

Before we estimate the above equation in log changes, we first estimate it in level changes where $\Delta \ln w_s$ and $\Delta \ln w^{\min}$ are replaced by Δw_s and $\Delta w^{\min}$, respectively. Table 2, Columns (1), (4), and (7) report estimation results for (absolute) firm wage changes and minimum wage changes for each firm size group, where small firms have less than 200 employees, medium size firms between 200 and 1,000 employees and larger firms more than 1,000 employees, respectively. A maximum likelihood-based non-linear least square (NLLS) estimation is used to infer the convexity parameter k separately for the sample of small, medium, and large firms. The three estimated parameters are relatively similar and statistically highly significant. The convexity parameter k is 0.313 for small firms compared to 0.426 and 0.391 for medium and large firms, respectively. A parameter of 0.31 implies that a low-wage firm facing a minimum wage of 80% of its average wage will be exposed 54% more (in absolute terms) to any minimum wage increase $[(0.8)^{0.31}/(0.2)^{0.31} = 1.54]$ compared to a high-wage firm for which the minimum wage represents only 20% of its average wage. Expressed in percentage terms relative to the firm wage, minimum wage impact is 6.15 times larger $[(0.8)^{1.31}/(0.2)^{1.31} = 6.15]$ for the low-wage firm. This underlines the significant heterogeneity of exposure to minimum wage changes across firms.

The panel regressions in Columns (2)-(3), (5)-(6), and (8)-(9) of Table 2 repeat the same specification in log terms, where the dependent variable is now the log average firm wage growth $\Delta \ln w_s$ and the minimum wage change is also expressed in log changes $\Delta \ln w^{\min}$. In these and all following regressions we infer the corresponding convexity parameters directly from the level regressions as $k + 1 = 1.313$, 1.426, and 1.391, because the log transformation increases the convexity of the impact function by one unit from $IF_s(k)$ to $IF_s(k+1)$.

The panel regressions in Columns (3), (6), and (9) feature firm fixed effects and thus allow for different growth trends of individual firm wages. Inclusion of firm fixed effects implies that the economic and statistical significance of the interaction term $\left[IF_s \times \Delta \ln w^{\min}\right]$ increases further. In Column (3), coefficient estimates $\widehat{\beta} = 2.085$ and $\widehat{\delta} = -0.219$ imply that for a 22% increase in the minimum wage $[\Delta \ln w^{\min} = 0.2]$, a small low-wage firm at the 10% wage quantile $(w_s/w^{\min} = 1.420)$ of the wage distribution increases its (log) average wage $\ln w_s$ by 21.9% $[= 2.085 \times (1.420)^{-1.313} \times 0.2 - 0.219 \times 0.2]$ compared to only 1% $[= 2.085 \times (4.781)^{-1.313} \times 0.2 - 0.219 \times 0.2]$ for a high-wage firm at the 90% wage quantile $(w_s/w^{\min} = 4.781)$. Hence, any minimum wage increase translates approximately one-to-one into an average firm wage increase for the low-wage firm.

The estimated (non-linear) relationship between a minimum wage increase and the average wage increase is similar for all three firm size groups. This is illustrated in Figure 3, which plots the convex impact function for small, medium, and large firms together with a histogram of the firm distribution of the firm wage relative to the minimum wage. For small and medium firms, the average wage increase is roughly 22% $[\Delta \ln w^{\min} = 0.2]$ for firms with an average wage close to the minimum wage $(w_s/w^{\min} = 1)$, which suggests that the non-linear impact function is correctly estimated at the low end of the wage distribution. For the large firm sample, we find point estimate for the average (log) wage effect somewhat larger than 20% close to the limit case with $w_s/w^{\min} = 1$, but the (bootstrapped) standard error are also higher for large firms.

Overall, we find that minimum wage changes have a highly heterogeneous effect on the average labor cost of Chinese manufacturing firms. This heterogeneous exposure can be proxied by the convex function $IF_s = \left(w_s/w^{\min}\right)^{-(k+1)}$, where the relative "closeness" of the minimum wage $w^{\min}$ to the average firm wage w_s determines the (non-linear) firm exposure to any further minimum wage increases. The effective firm exposure is given by the interaction term $IF_s \times \Delta \ln w^{\min}$ and can be used in reduced form regressions to capture the firm response to the labor cost shock.

While the interaction term $IF_s \times \Delta \ln w^{\min}$ allows for a more precise identification of the labor cost shock across firms with different average wages, it is (by construction) related to certain firm characteristics and cannot be considered a pure random assignment. In order to account for these differences between exposed and non-exposed firms and reduce the role of omitted variables, we include firm fixed effects in all reduced form specifications with a dependent variable defined in log growth rates.[13] Hence, we allow for the firm-specific growth trends of any dependent variable and identification comes entirely from a firm's time-varying exposure to minimum wage changes and particular of those low-wage firms with a high exposure term IF.

6 Evidence

6.1 Labor Substitution under Minimum Wage Shocks

Cost minimization implies that an adverse minimum wage shock provokes a labor to capital substitution for the most exposed low-wage firms. This labor substitution should occur independently of change in firm productivity in response to the adverse labor cost shock. Our identification relies on the interaction variable $IF_s \times \Delta \ln w^{\min}$, which captures the heterogeneous firm exposure under minimum wage shocks $\Delta \ln w^{\min}$. Any general correlation between minimum wage changes and changes in the capital to labor ratio of all firms is captured by the covariate $\Delta \ln w^{\min}$, and any cross-sectional growth differences for the capital to labor ratio related to low wage employment by the level covariate IF_s and by firm fixed effects. Our baseline regression for the change in the capital to labor ratio follows as

$$\Delta \ln(K/N)_{s,t} = \beta \ \left[IF_s \times \Delta \ln w^{\min}\right] + \gamma \ IF_s + \delta \ \Delta w^{\min} + \mu_{Ind\times Year} + \nu_s + \epsilon_{s,t}, \qquad (4)$$

[13]The DGMM estimator then uses again time differencing to eliminate the firm fixed effects and obtains consistent dynamic panel estimates.

where $\mu_{Ind \times Year}$ represents an interacted industry and time fixed effects and ν_s presents the firm fixed effects. The average trend rate of capital to labor substitution can therefore be firm specific.

In Table 3, Column (1) features both firm and time fixed effects, whereas Columns (2)-(8) use firm and interacted industry and time fixed effects. The latter specification can account any industry dynamics of the capital to labor ratio. The baseline regression in Column (2) yields a point estimate of 0.352 for the interaction term $IF_s \times \Delta w^{\min}$ as the main coefficient of interest. Let us consider a 22% [$\Delta \ln w^{\min} = 0.2$] increase in the minimum wage for a low- and high-wage firm at the 10% and 90% quantile of the distribution for $w_s/w^{\min}$ with values for the impact factor of 0.629 and 0.120, respectively. The firm difference in the labor to capital substitution follows as 3.58% [$= 0.352\times$ $(0.629 - 0.120)$ $\times 0.2$], compared to an annual average substitution rate of 9.0%. Hence, a minimum wage increase by 22% accelerates the labor to capital substitution by approximately four month (of trend substitution) for the most affected firms.

We can also compare the estimate of 0.352 for the average labor to capital substitution under the treatment effect $IF_s \times \Delta \ln w^{\min}$ to the corresponding coefficient of 2.085 for the average wage growth [see Table 2, Column (3)]. Under fully flexible input substitution and a Cobb-Douglas production function, both coefficients should be identical as

$$\Delta \ln(K/N)_{s,t} = \Delta \ln w_{s,t} \approx IF_{s,t} \times \Delta \ln w^{\min}. \tag{5}$$

The observed average adjustment in the capital to labor ratio is only 1/5 of the predicted change. For the foreign-owned firms, the corresponding point estimate of 0.728 in Column (7) brings us closer to the fully flexible benchmark. This stronger capital-labor substitution effect for foreign-owned firms can be explained by more vigorous capital investment under minimum wage shocks as shown in Section 6.2.

The standard errors reported in parentheses are clustered at the county-year unit, which corresponds to the treatment effect. However, the convexity parameter k in the impact function IF_s represents an estimated value which could render the standard errors in the main regression inaccurate. To correct for the estimated regressor problem, we also report (block) bootstrapped standard errors in brackets which are obtained by 500 sample draws with the county as the block unit and re-estimation of the parameters k for each sample draw. However, the bootstrapped standard errors tend to be only slightly larger and do not substantially affect the high level of statistical significance for the variable of interest.

Column (3) of Table 3 reports regression results for a dynamic panel specification estimated by (difference) GMM. The lagged dependent variable is instrumented with its own lagged value (at lag 2), while all other right-hand side variables are included directly in the instrument set and are thus treated as exogenous. The estimated coefficient for the lagged dependent variable is at -0.08 economically small and we obtain at 0.336 a very similar estimates for the interaction term $IF_s \times \Delta \ln w^{\min}$. As we find only a modest negative autocorrelation of the dependent variable, we focus on the LSDV regression as our preferred specification.

To explore sample heterogeneity with respect to firm size and initial TFP level (at the first firm observation), we define additional dummies (D_x) marking SOEs, private-owned, and foreign-owned firms as well as firms with low (below median) and high (above median) TFP, respectively. Using triple interactions in Columns (4) and (5) with the respective subsample dummies, we can decompose the coefficient β according to the contribution of each firm partition. The point estimates in Column (4) show the strongest labor to capital substitution for foreign-owned firms, followed by private-owned firms, and no statistically significant change for SOEs. We note that this pattern of response to the labor cost shock cannot be influenced by any pass-through of wage changes to product prices as the latter do not enter into the calculation of the capital to labor ratio. When sorting firms by their initial TFP level in Column (5), no significant difference in labor substitution is found.

Columns (6)-(8) repeat the regression for the subsamples of SOEs, foreign-owned firms, and exporters. The estimated substitution effects in the subsamples are almost identical to the respective point estimates in the pooled regression in Column (4). Exporters show the same large labor substitution under the minimum wage shocks as foreign-owned firms.

6.2 Production Response to Minimum Wage Increases

Next, we explore the minimum wage effect for (value added) firm output, labor input, and capital employed. Unlike the change in the capital to labor ratio, the predicted effects are ambiguous for output and input measures and depend on the endogenous response of total factor productivity to the adverse labor cost shock. In the absence of any differential change in total factor productivity for low-wage firms, firm output and inputs for employment and capital should all decrease because a low-wage firm faces an increased competitive disadvantage following a minimum wage increase. However, a strong endogenous increase in total factor productivity can overturn these predictions: if total factor productivity increases more for low-wage firms under the new adverse labor market conditions, output of the low-wage firm can remain constant or even increase in spite of a labor input decrease.

In Table 4, we present the dynamic panel regressions, where the specifications follow the previous setup in Table 3, Columns (4) and (5) with interaction dummies D_x. Formally,

$$\begin{aligned}\Delta \ln Z_{s,t} \quad = \quad & \sum_x \beta_x \; \left[IF_s \times \Delta \ln w^{\min} \times D\_x\right] + \sum_x \delta_x \; \left[\Delta \ln w^{\min} \times D\_x\right] + \\ & + \sum_x \gamma_x \; \left[IF_s \times D\_x\right] + \sum_x \theta_x \; D\_x + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}, \end{aligned} \tag{6}$$

where $Z_{s,t} = Y_{s,t}$, $N_{s,t}$, $K_{s,t}$, denote (value added) firm output, labor input (employment), and capital, respectively. The dummies D_x mark alternatively SOEs (D_SOE), private-owned firms ($D\_private$) and foreign-owned firms ($D\_foreign$) in Columns (2), (5), and (8); or low-TFP and high-TFP firms (based on initial levels marked $D\_low\ TFP$ and $D\_high\ TFP$, respectively) in Columns (3), (6), and (9). We report in parentheses robust standard errors for the one-step estimator clustered at the county/city-year unit and (block) bootstrapped standard errors in brackets accounting for the error in the estimated covariate IF_s.

In Table 4, Column (2), foreign-owned firms show a statistically significant positive coefficient $\widehat{\beta}_{foreign} = 0.509$ for (value added) output growth, compared to $\widehat{\beta}_{private} = 0.182$ for private-owned firms. By contrast, SOEs do not feature any accelerated output growth when exposed to a large minimum wage shock with $IF_s \times \Delta \ln w^{\min} \gg 0$. None of the three firm types shows any average decrease in the value added output for the most adversely affected firms as economic theory predicts in the absence of relative productivity increases in low-wage firms. Column (3) reveals that the output growth acceleration is larger at 0.240 for firms initially below the median industry TFP, but the difference to the corresponding point estimate of 0.152 for firms above median industry TFP is not statistically significant.

Columns (4), (5), and (6) provide the corresponding results for employment growth as the dependent variable. The coefficients of interest for the interaction terms $IF_s \times \Delta \ln w^{\min} \times D\_x$ are uniformly negative and statistically significant for all three firm type groups with foreign-owned firms showing the largest relative employment growth reduction. A 22% increase in the minimum wage ($\Delta \ln w^{\min} = 0.2$) reduces relative employment growth for foreign-owned low-wage firms (at the 10% quantile where $w_s/w^{\min} = 1.568$) by -4.7% [$= -0.424 \times (1.568)^{-1.313} \times 0.2$] compared to -0.8% [$= -0.424 \times (5.822)^{-1.313} \times 0.2$] for high-wage firms (at the 90% quantile where $w_s/w^{\min} = 5.822$) in the same industry sector. From Column (6) we infer that the relative employment growth reduction is 63% larger [$= (0.243/0.155) - 1$] for firms with below median (initial) TFP than for those with above median TFP.

Columns (7)-(9) of Table 4 document the minimum wage effect on changes in the capital stock. Unlike SOEs, private-owned and foreign-owned firms at the low end of the wage spectrum show a statistically significant growth in their capital stock in the year of the minimum wage hike. We find evidence for increased capital spending for firms (initially) both above and below the median industry TFP level.

Overall, the endogenous firm response to the minimum wage increase is at odds with the predicted relative decrease in output growth under constant firm productivity growth. Particularly, private-owned and even more so for foreign-owned firms feature accelerated output growth and reduced employment growth in the year of the minimum wage increase which points to a productivity leap. For cost shares of 2/3 and 1/3 for labor and capital, respectively, the estimates in Table 4 predict an average productivity increase for low-TFP firms given by

$$\frac{\Delta \ln A}{IF_s \times \Delta \ln w^{\min}} = \Delta \ln Y - \frac{2}{3}\Delta \ln N - \frac{1}{3}\Delta \ln K = 0.24 + \frac{2}{3} \times 0.253 - \frac{1}{3} \times 0.131 = 0.365. \quad (7)$$

We highlight that approximately half of the predicted productivity increase for low-TFP firms is accounted for by labor input reductions. This labor input reduction is not subject to any output price mismeasurement as employment is observed directly. The following section estimates the productivity effect of minimum wage shocks directly based on firm level productivity measures.

6.3 Total Factor Productivity and Minimum Wage Shocks

Productivity measurement is based on a Cobb-Douglas production function which combines inputs in capital K and labor L to generate value added output $Y_{s,t} = \mathit{Gross\ Revenue}_{s,t}/p_Y-$

Cost Intermediate Goods$_{s,t}/p_X$, where p_Y and p_X denote industry-level output and input price indices, respectively. We define the change in total factor productivity $\Delta \ln A_{s,t}$ as the change in the log difference between value added output and the value of labor input and capital using the factor shares α_L and $\alpha_K = 1 - \alpha_L$; that is

$$\begin{aligned} \Delta \ln A_{s,t} &= \ln A_{s,t} - \ln A_{s,t-1} = \\ &= \ln Y_{s,t} - \ln Y_{s,t-1} - \alpha_L(\ln w_{s,t-1}N_{s,t} - \ln w_{s,t-1}N_{s,t-1}) - \alpha_K(\ln K_{s,t} - \ln K_{s,t-1}). \end{aligned} \tag{8}$$

To discard any direct price effect of the minimum wage increase on the TFP measurement, we use lagged average wages w_{t-1} to evaluate the total labor costs $w_{t-1}N_t$ in period t.

Measurement of the parameters α_L and α_K of the production function is sensitive to reporting and measurement errors in firm input and output. We find that output regressions on factor inputs or more advanced estimation techniques (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015) produce a higher dispersion of parameter estimates with more implausible estimates for some firms. We therefore prefer the revenue share based inference as the more robust method to infer the production parameters α_L and α_K. In the absence of adjustment costs, cost minimization implies that the factor shares should be proportional to the cost share of labor and capital, hence the labor and capital shares follow as

$$\alpha_L = \frac{w_{s,t-1}N_{s,t}}{w_{s,t-1}N_t + (r_s + \delta_s)K_{s,t}} \quad \text{and} \quad \alpha_K = \frac{(r_s + \delta_{s,t})K_{s.t}}{w_{s.t-1}N_{s,t} + (r_s + \delta_{s,t})K_{s,t}}, \tag{9}$$

respectively. For the cost of capital we use an interest rate of $r_s = 7\%$ for all large firms, $r_s = 7.7\%$ for medium size firms, and $r_s = 8.4\%$ for small firms.[14] Added to the capital costs is capital depreciation $\delta_{s,t}$ inferred from the yearly accounting depreciation of each firm.

Our baseline results use TFP growth $\Delta \ln A1_{s,t}$ based on the time series average of $\alpha_{L/K}(s,t)$ for all observations available for the same firm. Alternative measures for the calculation of the factor shares are discussed in the Internet Appendix to this paper and produce quantitatively similar results. Inferring the factor shares from cost shares has the advantage that the inference is relatively robust to measurement errors. Output $\ln Y_{s,t}$ does not even enter the calculation,

[14]The interest rate of 7% was the benchmark (minimum) corporate bank loan rate during the period of 2002–08 and could increase to a maximum of 8.4%. We assume that small size firms paid the maximum rate and medium size firms a rate between the minimum and the maximum. Variations in these assumptions do not qualitatively change any of the results.

rendering any respective mismeasurement irrelevant. Moreover, any regression-based inference about factor shares is based on minimizing squared mean deviations so that misreported outliers can severely distort the inference while simple averaging over values of $\alpha_{L/K}(s,t)$ represents a more robust linear operation.

As before, we use a panel specification for TFP growth $\Delta \ln A1_{s,t}$ with the interaction term $IF_s \times \Delta \ln w^{\min}$ as the main regressor of interest. The corresponding level effect for the firm-specific impact function IF_s and the county-level minimum wage change $\Delta \ln w^{\min}$ are included as control variables in the specification

$$\Delta \ln A1_{s,t} = \beta \left[IF_s \times \Delta \ln w^{\min} \right] + \gamma \, IF_s + \delta \, \Delta \ln w^{\min} + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}, \tag{10}$$

where $\mu_{Ind \times Year}$ denotes the interacted industry and year fixed effects. As firms can differ in their productivity trend growth, we also include firm fixed effects ν_s in the specification. Inclusion of firm fixed effects means that β identifies the productivity growth acceleration in the year of the minimum wage hike to the extend that firms experiences an average wage cost increase proxied by $IF_s \times \Delta \ln w^{\min}$.

Table 5, Column (1), reports the Least Square Dummy Variable (LSDV) regression with firm and time fixed effects, whereas Columns (2)-(8) include firm fixed effects and interacted industry and time fixed effects. The positive productivity effect for low-wage firms is statistically significant in Column (2) with a point estimate $\widehat{\beta} = 0.211$ in the overall firm sample. This estimate is compatible with the results from Table 4, where the output, employment and capital components add up to an average productivity effect of

$$\frac{\Delta \ln A}{IF_s \times \Delta \ln w^{\min}} = \Delta \ln Y - \frac{2}{3} \Delta \ln N - \frac{1}{3} \Delta \ln K = 0.173 + \frac{2}{3} \times 0.195 - \frac{1}{3} \times 0.156 = 0.251. \tag{11}$$

Column (3) reports a dynamic panel specification and shows that productivity growth features a modest trend reversion. Yet the DGMM estimate for the interaction term are similar at $\widehat{\beta} = 0.178$ and statistically significant even if we account for the intertemporal reversion of firm productivity growth to its long-run (firm specific) trend.

More interesting still are the results which decompose this average effect by firm type and initial TFP level in Columns (4)-(5). We find a particularly strong endogenous productivity response for foreign-owned firms with a coefficient $\widehat{\beta}_{foreign} = 0.655$. This point estimate implies that a minimum wage increase of 22% [$\Delta \ln(w^{\min}) = 0.2$] increases productivity of a low-wage firm (at the 10% quantile where $w_s/w^{\min} = 1.568$) by 7.3% [$= 0.655 \times (1.568)^{-1.313} \times 0.2$] compared to 1.3% [$= 0.655 \times (5.822)^{-1.313} \times 0.2$] for a high-wage firms (at the 90% quantile where $w_s/w^{\min} = 5.822$) in the same industry sector. By comparison, the average annual TFP growth among foreign-owned firms is 9.2%. The additional TFP growth of 7.3% for low-wage firms therefore accounts for a growth acceleration equivalent to approximately nine months of trend growth in productivity. Private-owned firms also show a statistically significant acceleration of their productivity growth, albeit at a smaller magnitude. By contrast, there is no evidence for a stronger productivity growth of SOEs when exposed to minimum wage shocks. As a robustness check, we also undertake subsample regressions for SOEs and foreign-owned firms. The point estimates for the subsamples are very similar to the corresponding coefficients in Column (4) at $\widehat{\beta}_{SOE} = 0.017$ for SOEs [Column (6)] and $\widehat{\beta}_{foreign} = 0.645$ for foreign-owned firms [Column (7)].

We also find evidence that firms with low initial TFP levels feature stronger TFP growth when exposed to a minimum wage shock. In Column (5), the triple interaction term with the dummy $D\_low\text{-}TFP$ has a coefficient twice as large as the corresponding term interacted with the dummy $D\_high\text{-}TFP$. The coefficient $\widehat{\beta}_{low\text{-}TFP} = 0.307$ is again close to the productivity growth effect of 0.365 predicted in Section 6.2 based on output and input components. A low initial firm TFP implies that a firm has more scope to increase productivity as it is further from the industries' efficient frontier. To isolate this "productivity catch-up effect" from the "ownership effect", we double sort firms by their initial TFP into a high- and low-TFP subsample and then by ownership type. Table A6 in the Internet Appendix reports the corresponding regression: foreign-owned firms with a low initial TFP experience show by far the largest TFP acceleration. By contrast, SOEs do not exhibit any economically significant productivity improvement under minimum wage shocks even if their initial TFP is low. Figure 4 provides a graphical illustration of the quantitative importance of minimum wage increases for the acceleration of firm productivity growth. The graph shows the large difference in the estimated productivity growth between a low-wage and a high-wage firm implied by a 22% minimum wage increase [$\Delta \ln w^{\min} = 0.2$] for firms of different ownership types and initial TFP level (below versus above median). Low productivity firms under foreign ownership show by far the largest relative TFP gain.

Even though the treatment effect of the minimum wage change operates at the county-year level, we can nevertheless add country-year fixed effects because we still achieve identification by comparing more to less exposed firms based on their different average wage level. In Table A7 of the Internet Appendix, we re-estimate Table 5 with additional county-year effects and find very similar point estimates for all coefficients at similar levels of statistical significance. The county-year fixed effects can control for additional county-level dynamics uncorrelated to the minimum wage change itself. However, the qualitative results are robust.[15]

A concern about productivity evidence is mismeasurement of value added TFP. In particular, pass-through of minimum wage increases to product prices may imply a firm-specific product price inflation which is not correctly captured by the industry level price deflator. We highlight three findings which are difficult to reconcile with such a pass-through hypothesis. First, we document in Section 7 that exporting firms do not increase their exporting prices when confronted with minimum wage increases. Instead, the independently collected data of the Chinese customs authorities show an increase in export quantity which is consistent with our finding of an output and productivity increase. Particularly for foreign-owned firms can we exclude any economically significant wage pass-through to export prices. Second, if wage pass-through were to account for the productivity effects under minimum wage shocks, we would expect to find a spurious TFP increases in less competitive industries dominated by SOEs. However, SOEs show no evidence of such a TFP increase. Instead, the TFP increase shows up strongest among exporters where the pass-through hypothesis can be discarded. Third, the measured productivity surge in foreign- and private-owned firms is matched by a similar cross-sectional pattern of labor substitution and labor input reduction where output price measurement is not an issue.

We conclude that price mismeasurement cannot account for the cross-sectional pattern of productivity changes in Table 5. Instead, this evidence supports a narrative of X-inefficiency where only private-owned and foreign-owned firms meet the challenge of the labor cost shock and restructure accordingly. Such restructuring also involves more capital expenditure, as shown in Table 4, Column (8). Private-owned and particularly foreign-owned firms increase their capital

[15] The same robustness statement also applies to Tables 6 and 7 reported with county-year fixed effects in the Internet Appendix as Tables A6 and A7.

expenditure under an adverse labor cost shock, but no such reaction is seen for SOEs. We note that capital constrains cannot account for these differences as Chinese SOEs generally face better credit access than private-owned firms. The faster shock adjustment of private sector firms does not directly inform us about their overall contribution to China's manufacturing growth. Yet such higher responsiveness to market conditions is broadly consistent with evidence that roughly 70-80% of the aggregate growth in China's manufacturing sector between 1998 and 2007 was contributed by private sector firms (Hsieh and Song, 2015).

6.4 Productivity Effect by Management Practice

The particularly strong TFP response of foreign firms to adverse labor cost shocks could be explained by "better" or simply more structured management practices in these firms. While foreign ownership is the ultimate cause, differences in management practices could represent a proximate cause for the observed heterogeneous firm response to labor cost shocks. To explore this interpretation of the evidence further, we draw on survey data about management practices in 564 Chinese firms sampled in 2006, 2007, 2008, and 2010 by Bloom and van Reenen (2010). The data are based on telephone interviews that evaluate the quality of firm management in three dimensions: (1) monitoring practices (the collection and processing of production information); (2) target-setting practices (the ability to set coherent, binding short- and long-term targets); and (3) incentive practices (merit-based pay, promotion, hiring, and firing).[16] Responses along these three dimensions of management practice are then aggregated to a firm-specific management score.

We are able to match 460 firms and 538 survey observations to our firm data. To make the survey scores more comparable, we transform them into conditional measures which adjust for firm size (log employment), industry fixed effects and sample year fixed effects. As the survey scores do not have a straightforward cardinal interpretation, it is appropriate to express them as z-scores. Figure 2 provides the average conditional z-scores of various management practices in SOEs, private-owned and foreign-owned firms, respectively. The total management score in foreign-owned firms is on average 46% (25%) of one standard deviation higher than in SOEs (private-owned firms), which amounts to an economically and statistically significant difference.

[16] Compare Bloom *et al.* (2010) and Bloom and van Reenen (2007, 2010).

In order to evaluate if differences in management practices can account for the heterogeneous firm response to labor cost shocks, we extrapolate the survey scores to the full firm sample. Here we use a simple linear regression model that explains the survey observations as a linear function of three ownership types (SOE, private, foreign) and firm size (log employment) as well as year and industry fixed effects. Assuming the representativeness of the survey sample, we then predict the management scores ($Mgmt\_Score$) of all other firms based on firm ownership type and firm size and the fixed effects.[17] To adjust the standard errors for estimated regressor problem we jointly bootstrap the linear prediction and the second stage regression. Of course we cannot exclude that the linear prediction could reflect firm characteristics other than management quality if those also covary with ownership type and firm size. We also check directly if variations in management practices help to predict the ownership type of Chinese firm. This is indeed the case and documented in Table A12 of the Internet Appendix.

Table 6 replaces the ownership dummies in Table 5 by the (predicted) management score to explore whether this can account for the heterogeneous firm response to adverse labor shocks. The coefficient of interest is the triple interaction term $IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$, which we estimate for the full sample in Columns (1)-(3), for the sample of low-TFP firms in Columns (4)-(6) and for high-TFP firms Columns (7)-(9). For each sample, we report two LSDV specifications and the dynamic panel specification using the DGMM estimator. Low-TFP firms show the strongest association between predicted management quality and the increase in firm productivity under the adverse minimum wage shock. The point estimate of 1.638 for the triple interaction term in Column (5) implies that an increase in the variable $Mgmt\_Score$ by two standard deviations ($= 0.394$) under a (relative) minimum wage shock of $IF_s \times \Delta \ln w^{\min} = 0.102$ implies a TFP acceleration of 6.6% in the year of the minimum wage increase.[18] The estimated relationship between the incremental TFP growth of low-TFP firms and the triple interaction term $IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$ is graphically illustrated in a residual plot shown in Figure 5.

[17] This is like the first stage in a 2SLS estimation where ownership type and firm size are the instruments for the predicted values used in the second stage. We note that this first-stage prediction does not suffer from a weak instrument variable problem: The F-statistics for the regressors is 14.75 and its R^2 is 0.24. The results of the first stage regression are reported in Table A13, Column (1), of the Internet Appendix.

[18] The minimum wage exposure difference between a low wage firm at the 10% quantile and a high wage firm the 90% quantile of the impact function IF_s is 0.51. Multiplication by a minimum wage increase of 22% [$\Delta \ln w^{\min} = 0.2$] results in $IF_s \times \Delta \ln w^{\min} = 0.102$.

The sample difference for $Mgmt\_Score$ between foreign-owned firms and SOEs is 0.173. Multiplied by the point estimate of 1.638 and assuming a minimum wage shock of $IF_s \times \Delta \ln w^{\min}$ = 0.102, we obtain a differential productivity growth between foreign-owned firms and SOEs of only 2.9%, which is less than the incremental productivity growth difference of 8.1% shown Figure 4 for low-TFP firms. The lower economic significance of the triple interaction term is not so surprising. Measurement errors related to the survey data and prediction errors in the extrapolation to the full sample imply that the variable $Mgmt\_Score$ is only a proxy for the true management quality of Chinese firms. Both errors should attenuate the point estimate for the triple interaction term. To adjust the corresponding standard error for the estimated regressor problem, we jointly bootstrap the predictive regression based on the survey sample and block bootstrap the main LSDV or DGMM regression to obtain valid standard errors reported in brackets. For low-TFP firm in Columns (5), we still obtain statistical significance for the coefficient of interest at the 1 percent significance level, even if its economic significance is presumably underestimated.

Measurement errors related to the survey data and prediction errors in the extrapolation to the full sample imply that the variable $Mgmt\_Score$ is only a proxy for a firm's true management quality. Both errors should attenuate the size of the point estimate. To adjust the corresponding standard error for the estimated regressor problem, we jointly bootstrap the predictive regression based on the survey sample and block bootstrap the DGMM regression to obtain valid standard errors reported in brackets. For low-TFP firm in Columns (3) and (4), we still obtain statistical significance for the coefficient of interest at the 5 percent significance level.

Overall, the evidence supports the interpretation that management practice represents an important determinant for a successful endogenous firm response to minimum wage shocks. More structured management practices appear to be particularly valuable if the competitive pressure increases thus implying that they are in a complementary relationship with competitive forces.

7 Robustness

The output and TFP measures used so far are imputed using the industry price deflator. This is likely to generate a positive measurement bias if the pass-through of factor price changes—including the minimum wage increase itself—is firm-specific and not correctly captured by the industry-specific price deflator. Thus, the output or TFP growth could be overestimated precisely in cases where firms face a large labor cost increase. To discard such an output mismeasurement hypothesis, we draw on Chinese customs data that allows a decomposition of the export value into a volume and a price component at the firm level.

Table 7 reports panel regressions with changes in (log) export value ($\Delta \ln Exp\_Value$), changes in (log) export volume ($\Delta \ln Exp\_Volume$), and a change in the log unit prices ($\Delta \ln Exp\_Price$) as the dependent variable for 220,287 firm-year observations. Approximately, 64% of the observations concern foreign-owned firms and 4% SOEs. Columns (1), (4) and (7) show pooled results across all exporters: The minimum wage effect on export values is positive (though only statistically significant at the 10% level), but the effect is entirely due to increased trade volumes and not due to higher export prices as predicted by a pass-through hypothesis. The point estimate in Column (7) for the small price effect is -0.017 with a (bootstrapped) standard error of 0.096. This implies that firm-specific price inflation (under wage pass-through) can be excluded for exporting firms. Firm-specific output price effects (not captured by the industry price deflator) cannot account for the large productivity effect of 0.771 in Table 5, Column (8), as the latter is approximately eight standard deviations higher than the (near zero) point estimate of -0.017 for the output price effect.[19]

The decomposition of the value and volume effects by firm ownership in Columns (2) and (5) reveals that the export value and export volume expansion coinciding with minimum wage shocks is statistically significant (at the 5% level) for foreign-owned firms. This result is consistent with the finding in Table 5 that foreign-owned firms feature a large productivity leap when exposed to minimum wage shocks. SOEs and private-owned firms are less frequent among the exporters and accordingly their standard errors for volume and output price effects are much larger.

Non-exporting firms and particularly SOEs could enjoy more market power so that firm-

[19] As export price and volume statistical are independently collected by the Chinese custom authority, these are unlikely to share measurement errors with the Annual Survey of Industrial Firms (ASIF)

specific wage pass-through becomes more plausible. But this implies a positive estimation bias for the productivity growth of SOEs under minimum wage shocks—something we do not see confirmed in Table 5, Column (4) or (6). Also, any upward bias in the productivity measurement of SOEs further increases the differential productivity response to foreign-owned firms and will strengthen rather than weaken our key finding.

The economics literature provides mixed empirical evidence on the pass-through of minimum wage increases on output prices. In OECD countries, minimum wage changes mostly concern service sector employees and particularly restaurant workers. The non-tradeable nature of local services implies that pass-through is often found to be significant for food prices (Lemos, 2008). By contrast, local minimum wage shocks in China affect manufacturing firms with competitors in nearby locations which do not face a corresponding labor cost increase. The absence of (short-term) minimum wage pass-through within China's manufacturing sector appears plausible. Even for a national minimum wage introduced in the United Kingdom in 1999, Draca, Machin and van Reenen (2011) find no evidence of wage pass-through among listed firms.

Lastly, we addresses three additional robustness issues in Section C of the Internet Appendix to this paper. Section C.1 explores if alternative inference methods about the productivity parameters α_L and α_K of the production function (Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015) confirm the main results in the paper. Generally, our TFP measurement depends very little on inference about productivity parameter as much of the output increase around minimum wage hike comes simply from increased firm output. A second concern relates to systematic TFP mismeasurement across firm types, which is discussed in Section C.2. We argue that firm-type specific TFP measurement errors cannot easily account for the dynamic pattern of TFP surges around minimum wage increases. Finally, Section C.3 examines if firm exit can explain the productivity variation around minimum wage shocks. Here, we find that firm exit does not covary strong enough with local minimum wage shocks to qualify as an alternative explanation.

8 Conclusion

This paper explores the endogenous productivity response to adverse competitive shocks based on Chinese firm data from the manufacturing sector. The frequency and large cross-sectional variation of minimum wage shocks in China provide a unique opportunity to identify policy shocks exogenous to a firm's technological progress.

In line with neoclassical firm theory, we find that low-wage firms show a larger labor to capital substitution in the year of a minimum wage increase compared to high-wage industry peers. Yet their relative real output growth and market share is not diminished because the relative labor cost increase due to higher minimum wages is compensated for by higher firm productivity. We also find that this endogenous firm response if highly heterogeneous across firms and dependent on the ownership type of the firm: foreign-owned firms show the strongest TFP increase followed by private-owned Chinese firm, whereas state-owned enterprises (SOEs) show no evidence for an endogenous response to the labor cost shock. This low responsiveness of SOEs to changing labor market conditions may reflect a general lack of corporate agility which may be indicative of a larger competitive challenges of in the state-owned sector of the economy.

We carry the analysis one step further and interpret the evidence in the light of theories of firm productivity. Even though this part is of a more speculative nature, the evidence here is still very suggestive. Recent research shows that management practices (Bloom and van Reenen, 2010) correlate strongly with the level of firm productivity and many other firm measures of quality capacity (Bloom *et al.*, 2017). Complementary to this correlation evidence on productivity *levels* and management quality, the evidence in our paper concerns the *causal* and *dynamic* productivity adjustment to a competitive shock. We argue that management scores provide a proxy for a firm's "reactiveness" in terms of TFP improvement after an adverse labor cost shock: Higher management quality among private-owned and particularly foreign-owned firms (compared to SOEs), can account for this differential ability to meet the competitive challenge. In the light of the evidence, increased competition and management quality have a complementary relationship. But more research is needed on what precisely makes organizations and firms responsive to competitive challenges and causes productivity growth.

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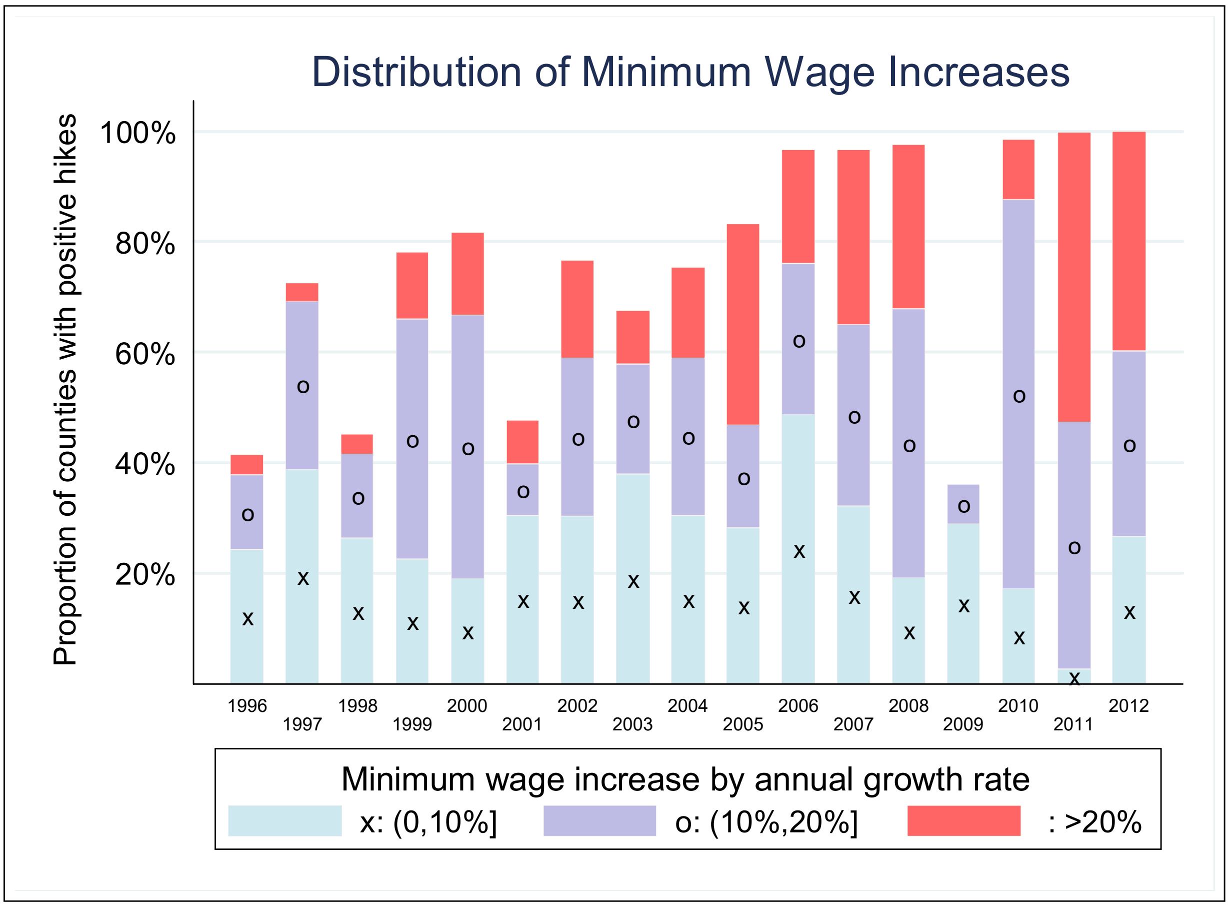

Figure 1: We plot by year the percentage of China's 2,867 counties with a strictly positive minimum wage change between 0 and 10%, between 10% and 20%, and above 20%, respectively.

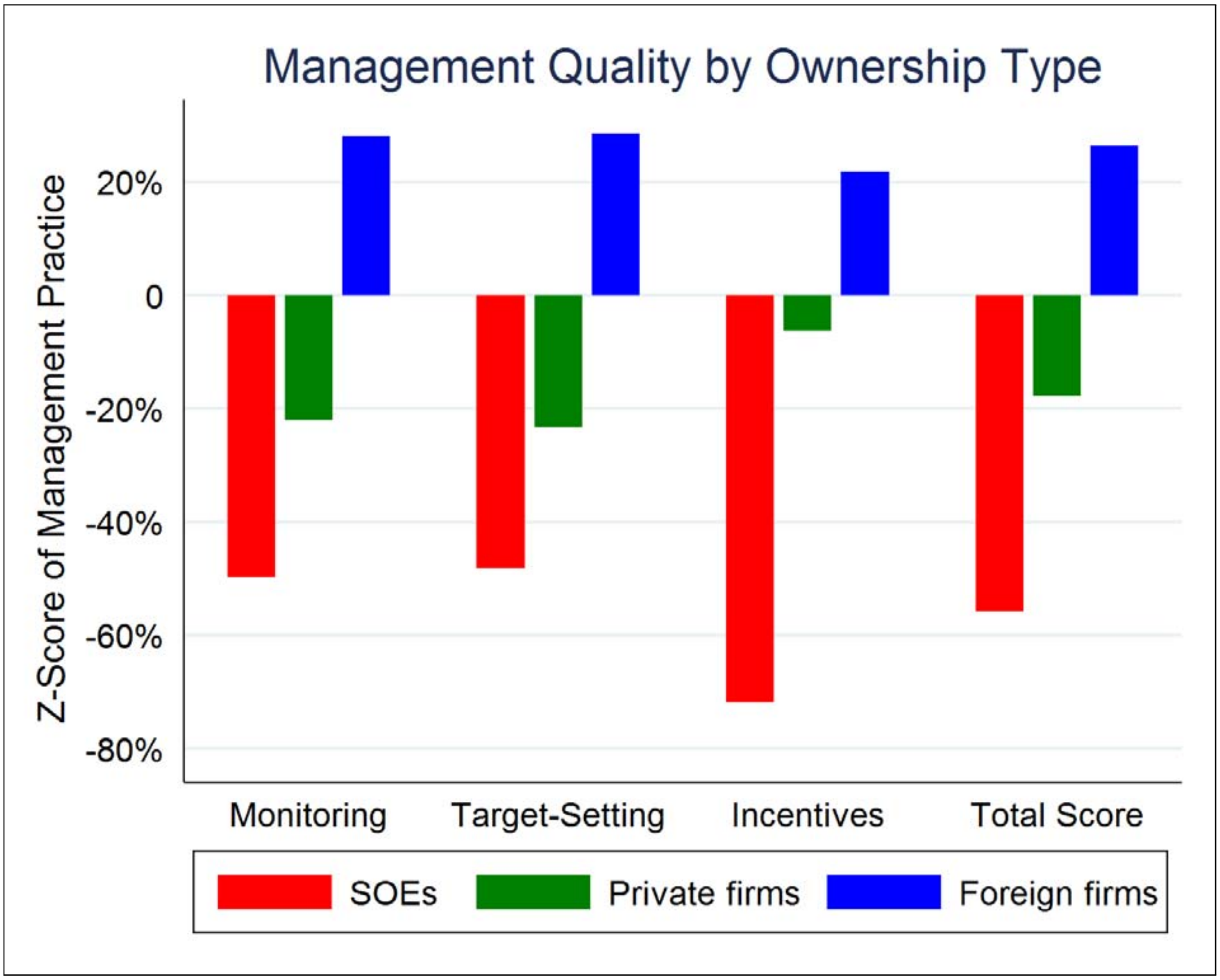

Figure 2: Based on survey data collected by Bloom and van Reenen (2010) on management practices in 564 Chinese firms sampled in 2006, 2007 and 2008, we report a breakdown of these scores by firm ownership (SOEs, private-owned firms, foreign-owned firms) after controlling for firm size and industry and sample year fixed effects. The conditional scores are expressed as z-scores relative to the conditional standard deviation for each dimension of measurement.

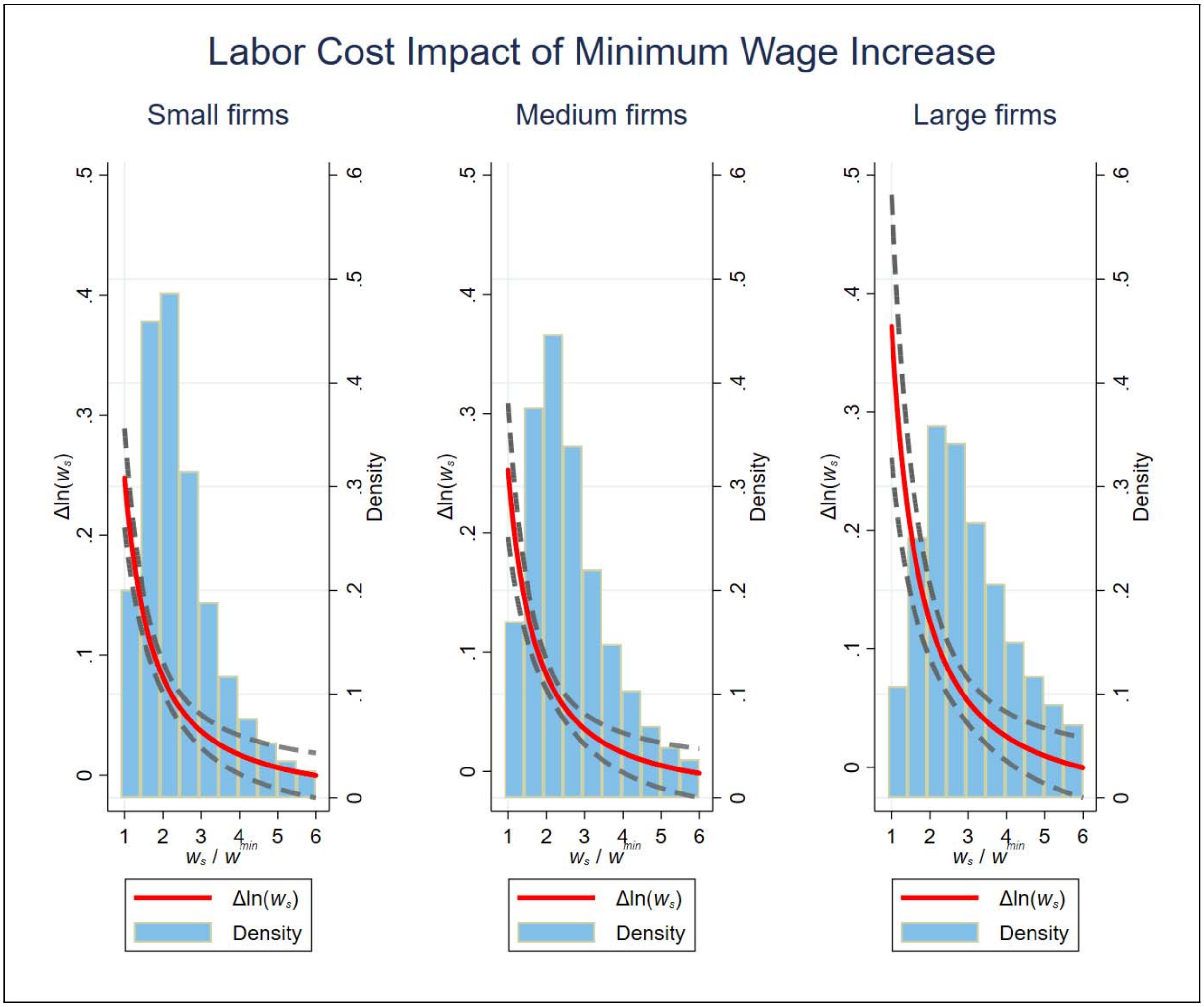

Figure 3: For small, medium, and large firms, we separately plot (on the left scale) the estimated (non-linear) average change in (log) firm wages $\Delta \ln w_s$ implied by a 22% minimum wage increase $[\Delta \ln(w^{\min}) = 0.2]$ as a function of the ratio $w_s/w^{\min}$ of the average firm wage w_s and the minimum wage $w^{\min}$ in year $t-1$. The histogram (on the right scale) provides the firm density distribution over the ratio $w_s/w^{\min}$.

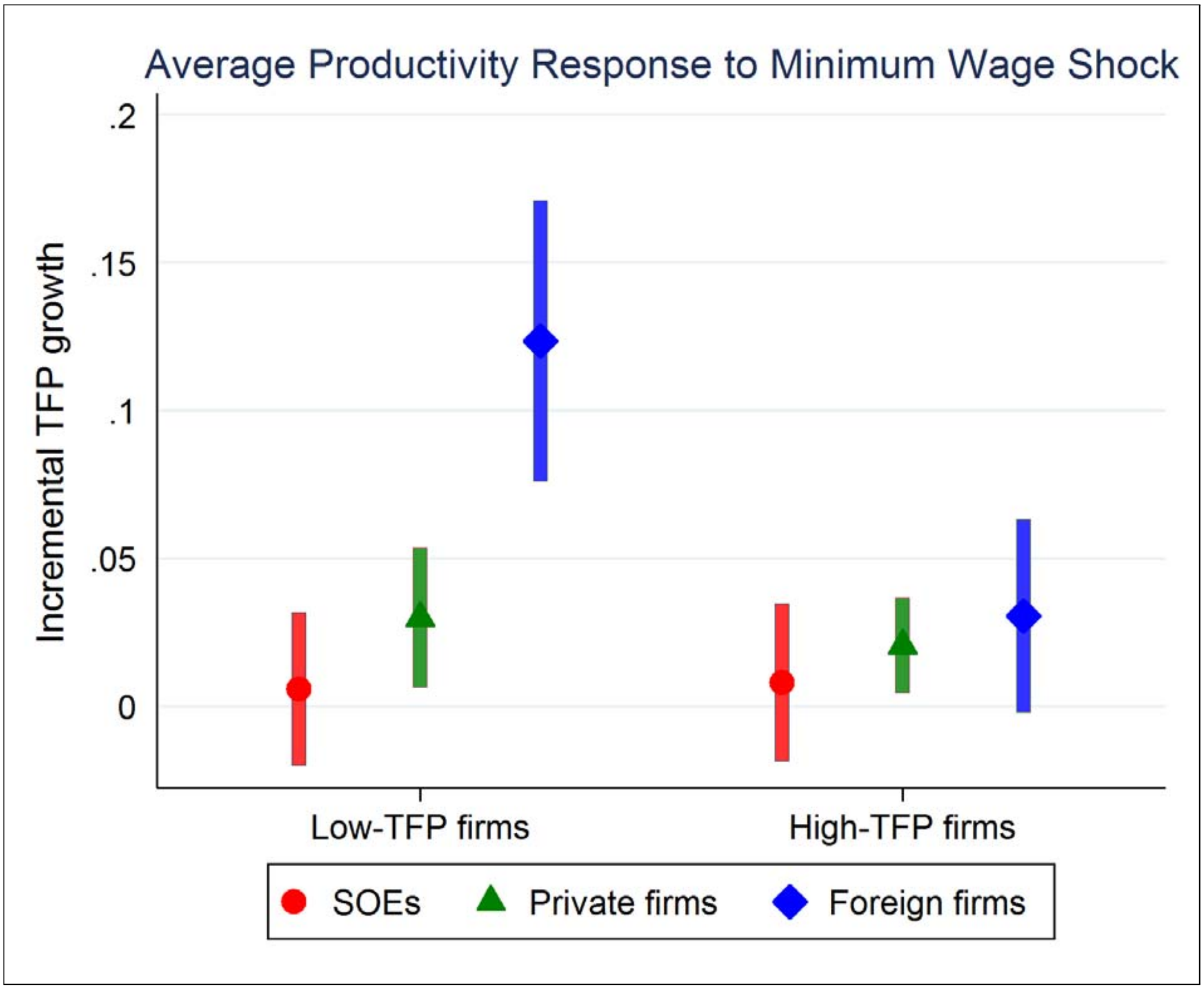

Figure 4: We plot the point estimates (and a two-sided bar of two standard deviations) for the incremental TFP growth resulting from a minimum wage shock of $IF_s \times \Delta \ln w^{\min} = 0.102$ for firms of different ownership type (SOEs, Private firms, Foreign firms) and below and above median TFP (Low-TFP firms versus High-TFP firms). The value of 0.102 is obtain for a 22% $[\Delta \ln w^{\min} = 0.2]$ minimum wage increase and a comparision of its impact between a low-wage firm (at the 10% quantile of its average firm wage relative to the local minimum wage) to a high-wage firm (at the 90% quantile), for which the interquantile range for IF_s is 0.51.

Figure 5: The residual plot based on Table 6, Column (5), shows the incremental TFP growth for low-TFP firms (i.e. firms below the median TFP level at the start of the sample) as a function of the triple interaction term $IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$, where the impact function IF_s measures firm exposure to the minimum wage change $\Delta \ln w^{\min}$ and $Mgmt\_Score$ represents the predicted total management score of a firm. Red points denote SOEs, green points private-owned firms and blue points foreign-owned firms.

Table 1: Summary Statistics

Panel A reports summary statistics for county-level (log) minimum wage changes for each year from 2002 to 2008. Panel B describes the firm characteristics for the full firm sample. We reported (annual) changes in the (log) capital to labor ratio $\Delta \ln(K/N)$, changes in the (log) (value added) output $\Delta \ln(Y)$, changes in (log) labor input $\Delta \ln(N)$, changes in the (log) capital stock $\Delta \ln(K)$, and changes with respect to two measures of total factor productivity $\Delta \ln(A1)$ and $\Delta \ln(A2)$. The impact function IF_s characterizes a firm's exposure to minimum wage changes. The predicted total management score of a firm is denoted $Mgmt\_Score$ and extrapolated from survey data provided by Bloom and van Reenen (2010). Based on Chinese customs data, we also report in Panel C summary statistics on the value and volume of annual exports for all exporting firms in China.

	Observations (1)	Mean (2)	STD (3)	Skewness (4)	Kurtosis (5)	P10 (6)	P50 (7)	P90 (8)
Panel A: Minimun wage changes (in logs) $\Delta \ln w_t^{\min}$								
2002	2,807	0.101	0.095	0.974	3.517	0.000	0.091	0.258
2003	2,809	0.064	0.069	1.038	3.519	0.000	0.048	0.170
2004	2,825	0.097	0.092	0.808	2.925	0.000	0.080	0.235
2005	2,821	0.131	0.103	0.699	3.662	0.000	0.118	0.255
2006	2,829	0.105	0.087	0.885	3.057	0.013	0.090	0.240
2007	2,772	0.143	0.091	0.680	2.886	0.035	0.118	0.281
2008	2,785	0.150	0.076	0.818	3.828	0.063	0.134	0.244
All years	19,648	0.113	0.093	0.781	3.320	0.000	0.097	0.240
Panel B: Firm statistics								
$\Delta \ln(K/N)$	1,201,803	0.090	0.480	0.899	6.305	−0.373	0.011	0.665
$\Delta \ln(Y)$	1,201,803	0.168	0.633	−0.081	4.413	−0.579	0.168	0.918
$\Delta \ln(N)$	1,201,803	0.027	0.301	0.290	6.217	−0.286	0.000	0.369
$\Delta \ln(K)$	1,201,803	0.117	0.432	1.654	8.951	−0.125	−0.010	0.619
$\Delta \ln(A1)$	1,201,803	0.101	0.635	−0.124	4.247	−0.664	0.112	0.852
$\Delta \ln(A2)$	1,201,803	0.104	0.632	−0.108	4.251	−0.656	0.112	0.853
$IF_s \times \Delta \ln w^{\min}$	1,201,803	0.038	0.040	4.972	82.030	0.004	0.030	0.081
$\Delta \ln w^{\min}$	1,201,803	0.110	0.073	0.745	4.030	0.018	0.104	0.213
IF_s	1,201,803	0.361	0.271	4.545	48.056	0.120	0.313	0.629
$w_s/w^{\min}$	1,201,803	2.951	1.895	3.053	18.895	1.436	2.428	4.991
$IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$	1,201,803	0.096	0.101	5.079	86.502	0.009	0.075	0.203
$Mgmt\_Score$	1,201,803	2.534	0.127	0.610	3.376	2.385	2.517	2.708
Panel C: Exporting firms								
$\Delta \ln Exp\_Value$	239,267	0.240	1.094	0.512	14.663	−0.668	0.169	1.276
$\Delta \ln Exp\_Volume$	231,842	0.309	1.169	1.379	14.388	−0.636	0.157	1.476
$\Delta \ln Exp\_Price$	231,842	−0.074	0.690	−4.452	53.942	−0.448	0.015	0.309

Table 2: Non-Linear Firm Wage Impact of Minimum Wage Changes

We estimate the non-linear effect of (log) minimum wage changes $\Delta \ln w^{\min}$ on the (log) average yearly wage change $\Delta \ln w_s$ of industrial firms grouped into small, medium, and larger firms. To capture asymmetric exposure to minimum wage changes, we define a minimum wage impact function $IF_s(k) = \left(w_s/w^{\min}\right)^{-k}$ that depends on the ratio $w_s/w^{\min}$ of the firm average wage and the minimum wage and a parameter k determining the convexity of the impact factor. The impact factor is interacted with the minimum wage changes. In order to estimate for the convexity parameter k, we first use in columns (1), (4), and (7) a maximum likelihood-based non-linear least square (NLLS) estimation based on wage changes Δw_s in levels and county/city-level minimum wage changes $\Delta w^{\min}$ also in levels. Columns (2)-(3),(5)-(6), and (8)-(9) then use the implied impact factor $IF_s(k+1)$ for log changes. Columns (3), (6), and (9) augment the specification with firm fixed effects. All regressions control for interacted industry and year fixed effects. Reported are robust standard errors adjusted for clustering at the county-year unit in parenthesis and (block) bootstrapped standard errors in brackets based on 500 replications. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	Small firms			Medium firms			Large firms		
	NLLS	FE	FE	NLLS	FE	FE	NLLS	FE	FE
	Δw_s	$\Delta \ln w_s$	$\Delta \ln w_s$	Δw_s	$\Delta \ln w_s$	$\Delta \ln w_s$	Δw_s	$\Delta \ln w_s$	$\Delta \ln w_s$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
k	0.313	$k+1$ fixed	$k+1$ fixed	0.426	$k+1$ fixed	$k+1$ fixed	0.391	$k+1$ fixed	$k+1$ fixed
	(0.011)***			(0.019)***			(0.050)***		
$IF_s(k) \times \Delta w^{\min}$	16.335			10.784			11.328		
	(0.574)***			(0.488)***			(1.430)***		
$IF_s(k)$	3.987			4.298			4.469		
	(0.045)***			(0.080)***			(0.256)***		
$\Delta w^{\min}$	−12.612			−7.284			−6.863		
	(0.557)***			(0.448)***			(1.310)***		
$IF_s(k+1) \times \Delta \ln w^{\min}$		0.861	2.085		0.544	1.845		0.881	2.414
		(0.126)***	(0.220)***		(0.125)***	(0.260)***		(0.201)***	(0.511)***
		[0.118]***	[0.213]***		[0.123]***	[0.296]***		[0.221]***	[0.569]***
$IF(k+1)$		0.707	1.347		0.662	1.162		0.638	1.304
		(0.014)***	(0.027)***		(0.016)***	(0.039)***		(0.029)***	(0.079)***
		[0.040]***	[0.142]***		[0.025]***	[0.092]***		[0.052]***	[0.197]***
$\Delta \ln w^{\min}$		0.037	−0.219		0.115	−0.128		0.064	−0.160
		(0.061)	(0.083)***		(0.046)**	(0.080)		(0.068)	(0.121)
		[0.060]	[0.101]***		[0.048]**	[0.097]		[0.076]	[0.137]
Ind. × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	682,954	682,954	599,225	244,647	244,645	216,984	38,913	38,911	35,440

Table 3: Labor to Capital Substitution and Minimum Wage Increases

Reported are the estimated effects of minimum wage changes $\Delta \ln w^{\min}$ on yearly changes in the capital to labor ratio $\Delta \ln(K/N)_{s,t}$ in Least Square Dummy Variable (LSDV) regressions. The specification features (1) an interaction terms of $IF_s \times \Delta \ln w^{\min}$ a firm's minimum wage impact function $IF(k)$ with the local minimum wage change $\Delta \ln w^{\min}$, (2) the minimum wage change $\Delta \ln w^{\min}$ itself and (3) the impact factor capturing a firm's (non-linear) sensitivity to minimum wage changes in a panel regression

$$\Delta \ln(K/N)_{s,t} = \beta \left[IF_s \times \Delta \ln w^{\min}\right] + \gamma \, IF_s + \delta \, \Delta \ln w^{\min} + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t},$$

where $\mu_{Ind \times Year}$ represents a set of interacted industry and year fixed effects. Column (1) featues firm and time fixed effects, whereas Columns (2)-(8) also have interacted industry and time fixed effects. Column (3) presents a dynamic panel specification estimated by (difference) GMM. As instruments we use the second lag of the dependent variable and all other regressors at zero lag. Columns (4) and (5) extend the LSDV regression to triple interaction terms with either three different ownership dummies (SOE, private-owned, foreign-owned) or two firm productivity dummies for low- or high-TFP firms, respectively. Columns (6)-(8) report subsample regressions for SOEs, foreign owned firms, and exporting firms, respectively. The minimum wage impact function $IF_s(k+1) = \left(w_s/w^{\min}\right)^{-(k+1)}$ depends on the ratio $w_s/w^{\min}$ of a firm's average wage (in year $t-1$) relative to the the minimum wage $w^{\min}$. The parameter k determines the convexity of the impact factor function. We use $k+1 = 1.332$, 1.434, and 1.399 obtained in Table 2 for small, medium, and large firms, respectively. The sample period is 2002-08. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county-year unit in parenthesis and (block) bootstrapped standard errors in brackets to account for the first-stage estimation of the IF_s term. The last row reports an F-test for equality of the tripple interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms					SOEs	Foreign	Exporters
	LSDV	LSDV	DGMM	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln(K/N)_{s,t-1}$			−0.080					
			(0.002)***					
$IF_s \times \Delta \ln w^{\min}$	0.360	0.352	0.336			0.112	0.728	0.722
	(0.046)***	(0.046)***	(0.046)***			(0.064)*	(0.103)***	(0.106)***
	[0.055]***	[0.055]***	[0.054]***			[0.072]*	[0.114]***	[0.122]***
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$				0.084				
				(0.063)				
				[0.069]				
$IF_s \times \Delta \ln w^{\min} \times D\_private$				0.345				
				(0.058)***				
				[0.065]***				
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$				0.716				
				(0.104)***				
				[0.113]***				
$IF_s \times \Delta \ln w^{\min} \times D\_low\ TFP$					0.384			
					(0.059)***			
					[0.067]***			
$IF_s \times \Delta \ln w^{\min} \times D\_high\ TFP$					0.322			
					(0.058)***			
					[0.067]***			
$\Delta \ln w^{\min}$	−0.055	−0.048	−0.058			−0.021	−0.143	−0.139
	(0.023)**	(0.023)**	(0.023)**			(0.023)	(0.041)***	(0.041)***
IF_s	0.162	0.165	0.153			0.146	0.151	0.169
	(0.006)***	(0.006)***	(0.006)***			(0.011)***	(0.012)***	(0.013)***
Interaction terms with D_x	No	No	No	Yes	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No	No	No	No	No
Ind. × Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,110,189	629,264	1,110,189	1,110,189	101,600	242,518	220,287
$AR(1)$			−145					
$AR(2)$			0.36					
H_0 : Equal interaction (p-value)				0.00	0.40			

Table 4: The Production Response to Minimum Wage Increases

We report panel regressions in which output changes [Columns (1)-(3)], labor input changes [Columns (4)-(6)], and capital input changes [Columns (7)-(9)] are explained by triple interaction terms $IF_s \times \Delta \ln w^{\min} \times D\_x$ of a firm's minimum wage impact function IF_s and the local minimum wage changes $\Delta \ln w^{\min}$ and firm dummies D_x, which can be either firm ownership dummies (SOE, private-owned, foreign-owned) or productivity dummies (low-TFP, high-TFP). The panel regression follows the specification

$$\Delta \ln Z_{s,t} = \sum_x \beta_x \ \left[IF_s \times \Delta \ln w^{\min} \times D\_x\right] + \sum_x \delta_x \ \left[\Delta \ln w^{\min} \times D\_x\right] + \sum_x \gamma_x \ \left[IF \times D\_x\right] + \sum_x \theta_x \ D\_x + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t},$$

where $Z_s = Y_s$, N_s, K_s, Π_s denote (value added) output, labor input (employment), capital, and profit, respectively. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county/city-year unit in parenthesis and (block) bootstrapped standard errors in brackets to account for the first-stage estimation of the IF term. The last row reports an F-test for equality of the tripple interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	Output change $\Delta \ln Y_{s,t}$			Labor input change $\Delta \ln N_s$			Capital input change $\Delta \ln K_{s,t}$		
	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IF_s \times \Delta \ln w^{\min}$	0.173			-0.195			0.156		
	(0.053)***			(0.034)***			(0.038)***		
	[0.056]***			[0.041]***			[0.044]***		
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$		-0.027			-0.089			-0.005	
		(0.090)			(0.050)*			(0.044)	
		[0.091]			[0.056]*			[0.044]	
$IF_s \times \Delta \ln w^{\min} \times D\_private$		0.182			-0.181			0.164	
		(0.064)***			(0.041)***			(0.048)***	
		[0.063]***			[0.048]***			[0.053]***	
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$		0.509			-0.424			0.293	
		(0.147)***			(0.076)***			(0.082)***	
		[0.156]***			[0.087]***			[0.093]***	
$IF_s \times \Delta \ln w^{\min} \times D\_low\ TFP$			0.240			-0.253			0.131
			(0.074)***			(0.043)***			(0.046)***
			[0.075]***			[0.048]***			[0.051]***
$IF_s \times \Delta \ln w^{\min} \times D\_high\ TFP$			0.152			-0.155			0.167
			(0.064)**			(0.041)***			(0.048)***
			[0.066]**			[0.050]***			[0.053]***
$\Delta \ln w^{\min}$	-0.034			0.032			-0.016		
	(0.029)			(0.015)**			(0.021)		
IF_s	0.124			-0.159			0.006		
	(0.007)***			(0.005)***			(0.004)		
All interaction terms with D_x	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$	$1,110,189$
H_0 : Equal interaction (p-value)		0.01	0.31		0.00	0.06		0.00	0.52

Table 5: Total Factor Productivity Growth after Minimum Wage Increases

We report least square regressions with dummy variables (LSDV) to capture the effect of minimum wage changes on the total factor productivity (TFP) growth measure $\Delta \ln A1_s$. The TFP measure $A1$ is calculated on the basis of a firm's cost share for labor and capital averaged over time. TFP growth is regressed on an interaction term $IF \times \Delta \ln w^{\min}$ of local minimum wage changes $\Delta \ln w^{\min}$ and a firm's minimum wage impact function IF capturing a firm's sensitivity to minimum wage increases. The regressors also include the separate terms effects $\Delta \ln w^{\min}$, and IF in the following specification

$$\Delta \ln A1_{s,t} = \beta \ \left[IF_s \times \Delta \ln w^{\min}\right] + \gamma \ IF_s + \delta \ \Delta \ln w^{\min} + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}.$$

Column (3) presents a dynamic panel specification estimated by (difference) GMM. As instruments we use the second lag of the dependent variable and all other regressors at zero lag. Columns (4) and (5) interact the term $IF \times \Delta \ln w^{\min}$ further with firm size and productivity dummies similar to Tables 4, 5, and 6. Columns (6) to (8) provide subsample results for large firms, low-TFP firms and exporting firms, respectively. Reported are robust standard errors adjusted for clustering at the county/city-year unit in parenthesis and (block) bootstrapped standard errors in brackets which account for the first-stage estimation of the IF term. The last row reports an F-test for equality of the tripple interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms					SOEs	Foreign	Exporters
	LSDV	LSDV	DGMM	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \ln A1_{s,t-1}$			−0.153					
			(0.003)***					
$IF_s \times \Delta \ln w^{\min}$	0.224	0.211	0.178			0.017	0.645	0.771
	(0.064)***	(0.063)***	(0.059)***			(0.102)	(0.168)***	(0.155)***
	[0.072]***	[0.072]***	[0.069]***			[0.105]	[0.185]***	[0.180]***
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$				0.031				
				(0.094)				
				[0.099]				
$IF_s \times \Delta \ln w^{\min} \times D\_private$				0.197				
				(0.074)***				
				[0.079]***				
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$				0.655				
				(0.169)***				
				[0.183]***				
$IF_s \times \Delta \ln w^{\min} \times D\_low\ TFP$					0.307			
					(0.083)***			
					[0.090]***			
$IF_s \times \Delta \ln w^{\min} \times D\_high\ TFP$					0.173			
					(0.074)**			
					[0.082]**			
$\Delta \ln w^{\min}$	−0.065	−0.039	−0.012			0.083	−0.054	−0.108
	(0.032)**	(0.032)	(0.030)			(0.041)**	(0.070)	(0.065)*
IF_s	0.210	0.212	0.156			0.167	0.224	0.209
	(0.008)***	(0.008)***	(0.008)***			(0.017)***	(0.020)***	(0.018)***
All interaction terms with D_x	No	No	No	Yes	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No	No	No	No	No
Ind. FE × Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,110,189	620,430	1,110,189	1,110,189	101,600	242,518	220,287
$AR(1)$			−131					
$AR(2)$			−3.86					
H_0 : Equal interaction (p-value)				0.00	0.16			

Table 6: Productivity Effect by Management Practice

We regress the management score of 548 Chinese firms in a survey sample by Bloom and Reenen (2010) on ownership type dummies and firm size (employment) and in a second step extrapolate the estimated model to all Chinese firms to obtain a predicted management score ($Mgmt\_Score$). The latter term is used in panel regression as an interaction term with $IF_s \times \Delta \ln w^{\min}$ to explain the heterogeneous total factor productivity (TFP) growth measure $\Delta \ln A1_s$. We report LSDV and (difference) GMM regressions. The latter use as instruments the second lag of the dependent variable and all other regressors at zero lag. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county/city-year unit in parenthesis and (block) bootstrapped standard errors in brackets which account for the first-stage estimation of the $Mgmt\_Score$ term. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms			Low-TFP firms			High-TFP firms		
	LSDV	LSDV	DGMM	LSDV	LSDV	DGMM	LSDV	LSDV	DGMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln A1_{s,t-1}$			-0.156			-0.165			-0.146
			(0.003)***			(0.003)***			(0.003)***
$IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$	1.020	1.063	1.014	1.484	1.638	1.383	0.577	0.616	0.810
	(0.415)**	(0.402)***	(0.371)***	(0.612)**	(0.591)***	(0.550)**	(0.495)	(0.484)	(0.468)*
	[0.397]**	[0.403]***	[0.401]***	[0.610]**	[0.608]***	[0.550]**	[0.536]	[0.535]	[0.554]*
$\Delta \ln w^{\min} \times Mgmt\_Score$	0.194	0.058	-0.038	-0.359	-0.480	-0.109	0.617	0.413	0.114
	(0.176)	(0.170)	(0.162)	(0.223)	(0.221)**	(0.206)	(0.234)***	(0.223)*	(0.213)
	[0.173]	[0.169]	[0.160]	[0.238]	[0.237]**	[0.216]	[0.235]***	[0.228]*	[0.223]
$IF_s \times Mgmt\_Score$	-0.173	-0.159	-0.185	-0.052	-0.044	-0.199	-0.244	-0.233	-0.200
	(0.053)***	(0.052)***	(0.049)***	(0.080)	(0.079)	(0.075)***	(0.058)***	(0.058)***	(0.057)***
	[0.100]***	[0.099]***	[0.086]***	[0.109]	[0.109]	[0.108]***	[0.110]***	[0.109]***	[0.093]***
$Mgmt\_Score$	-1.783	-1.746	-1.740	-1.211	-1.185	-1.431	-2.174	-2.129	-2.091
	(0.043)***	(0.043)***	(0.041)***	(0.056)***	(0.057)***	(0.052)***	(0.053)***	(0.052)***	(0.050)***
	[0.070]***	[0.070]***	[0.065]***	[0.074]***	[0.076]***	[0.076]***	[0.084]***	[0.084]***	[0.077]***
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes	No	No	Yes	No	No
Ind. FE × Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	1,110,189	1,110,189	620,430	520,230	520,228	293,867	589,959	589,958	326,563
$AR(1)$			-130			-99			-106
$AR(2)$			-4.44			-5.03			-1.65

Table 7: Exports Effects by Volume and Value

We use customs trade data to decompose the (log) firm export value into a (log) value component and a (log) price component. The log changes in export value, export volume, and export unit price are used as the dependent variables in same panel regression in Columns (1)-(3), (4)-(6), and (7)-(9), respectively. Columns (3), (6), and (9) include a lagged dependent variable estimated by (difference) GMM. The instrument set include the second lag of the dependent variable and all other regressors at lag zero. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county/city-year unit in parenthesis and (block) bootstrapped standard errors in brackets which account for the first-stage estimation of the IF_s term. The last row reports an F-test for equality of the tripple interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	Export value change $\Delta \ln Exp\_Value_{s,t}$			Export volume change $\Delta \ln Exp\_Volume_{s,t}$			Unit price change $\Delta \ln Exp\_Price_{s,t}$		
	LSDV	LSDV	DGMM	LSDV	LSDV	DGMM	LSDV	LSDV	DGMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln Exp\_XX_{s,t-1}$			-0.099			-0.061			-0.047
			$(0.007)^{***}$			$(0.006)^{***}$			$(0.007)^{***}$
$IF_s \times \Delta \ln w^{\min}$	0.318			0.240			-0.017		
	$(0.180)^{*}$			(0.194)			(0.098)		
	$[0.189]^{*}$			[0.211]			[0.096]		
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$		0.906	-0.481		0.744	-0.647		0.064	0.431
		(1.066)	(1.118)		(1.031)	(1.195)		(0.608)	(0.707)
		[1.097]	[1.222]		[1.072]	[1.247]		[0.580]	[0.669]
$IF_s \times \Delta \ln w^{\min} \times D\_private$		0.090	0.656		-0.173	0.269		0.205	0.192
		(0.316)	$(0.364)^{*}$		(0.336)	(0.375)		(0.182)	(0.246)
		[0.314]	$[0.386]^{*}$		[0.343]	[0.383]		[0.187]	[0.246]
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$		0.533	0.340		0.557	0.492		-0.142	-0.193
		$(0.214)^{**}$	(0.211)		$(0.234)^{**}$	$(0.231)^{**}$		(0.117)	(0.138)
		$[0.209]^{**}$	[0.184]		$[0.230]^{**}$	$[0.241]^{**}$		[0.117]	[0.154]
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	220,287	220,287	110,516	212,717	212,717	105,193	212,717	212,717	105,193
$AR(1)$			-33			-39			-27
$AR(2)$			-1.09			0.74			-0.45
H_0 : Equal interaction (p-value)		0.45	0.54		0.18	0.59		0.27	0.29

Internet Appendix

Firm Response to Competitive Shocks: Evidence from China's Minimum Wage Policy

Not for Journal Publication

Harald Hau

University of Geneva, CEPR, and Swiss Finance Institute*

Yi Huang

Graduate Institute, Geneva**

Gewei Wang

Peking University***

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*University of Geneva, GSEM, Geneva Finance Research Institute, 42 Bd du Pont d'Arve, 1211 Genève 4, Switzerland. Tel.: (++41) 22 379 9581. E-mail: prof@haraldhau.com. Web page: http://www.haraldhau.com.

**Graduate Institute of International and Development Studies, Maison de la paix, Chemin Eugène-Rigot 2, 1202 Genève, Switzerland. E-mail: yi.huang@graduateinstitute.ch.

***E-mail: geweiwang@gmail.com.

Internet Appendix

A. The Neoclassical Model with Labor Heterogeneity

Average firm wages vary across firms within the same industry and this partially reflects differences in average labor quality. In a competitive labor market, higher individual labor productivity translates into a higher wage. This allows for the coexistence of firms with low-skill and high-skill labor, where the high-skill firm employs fewer workers at a higher average wage. But such firm differences in the wage structure imply that a minimum wage increase has heterogeneous effects on the labor costs of individual firms, even if they are subject to the same regulatory change.

To explore this aspect in detail, we outline in Section A.1 a simple neoclassical model of labor input heterogeneity. A low-wage and high-wage firm face the same minimum wage increase, but adjust differently to the a minimum wage shock, $\Delta \ln w^{\min}$. In Section A.2, we characterize the profit optimizing input and output change following the cost shock in two propositions. Here we take firm productivity as exogenous. In Section A.3, we extend the neoclassical model to allow for frictions (or X-inefficiency) which prevents firms from reaching maximal productivity. We describes a *simple incentive structure* for managers which implies a higher TFP increase for the low-wage firm than for high-wage firm in reaction to higher minimum wages. The model can also explain the differential reaction of low-wage SOEs relative to low-wage private firms if incentive parameters are stronger in the latter. This rationalizes the results in Table 5.

A.1 Minimum Wage Shocks under Monopolistic Competition

Consider a two-period model in which two monopolistic firms, $s \in \{L, H\}$, produce goods L and H respectively. Let H denote the good produced with high-skilled labor at high average wages, whereas L is produced mostly with low-skill labor at a low average firm wage. The output of the two firms are described by a Cobb-Douglas production function in value added output. They combine inputs in capital K and labor L to generate value added output $Y_s =$ *Gross Revenue*$/p_Y -$ *Cost Intermediate Goods*$/p_X$, which is the difference between gross revenue (deflated by the industry price index p_Y) and the cost of intermediate good inputs (deflated by the intermediate goods price index p_X). Formally, the two production functions are given by

$$Y_L = A_L K_L^\alpha L_L^\beta \qquad \text{and} \qquad Y_H = A_H K_H^\alpha L_H^\beta, \tag{A1}$$

where the labor input L is the product of average labor quality Q and labor quantity N (employment) according to

$$L_L = Q_L N_L \qquad \text{and} \qquad L_H = Q_H N_H, \tag{A2}$$

respectively. In the absence of any minimum wage restrictions in the first period, average labor quality over the distribution of all firm employees is measured by the average wage with $Q_L = w_L < w_H = Q_H$ and labor quantity by the number of firm employees. While average labor quality and quantity are substitutes in the long run, we assume that the average labor quality Q is a fixed factor that cannot be changed in the short run.[1] A binding minimum wage introduced in period 2 drives a wedge between labor quality and the average wage. Only employment N and the capital stock K can adjust in period 2. For simplicity, we also assume constant returns to scale with $\alpha+\beta=1$ and that both firms face the same cost of capital and the same factor price for the intermediate good. The asymmetric use of low-skill labor by the two firms implies an unequal exposure to a minimum wage increase $\Delta \ln w^{\min} > 0$. Firm L, with its greater reliance on low-skill labor, suffers a larger increase in its average (log) wage $\Delta \ln w^L$ (without a corresponding increase in labor quality) than firm H; hence

$$\frac{\Delta \ln w_L}{\Delta \ln w^{\min}} > \frac{\Delta \ln w_H}{\Delta \ln w^{\min}}. \tag{A3}$$

Such asymmetric exposure of firms implies that the effect of minimum wage shocks is also heterogeneous and that an econometric identification procedure should account for this heterogeneity. Consider a unimodal distribution of employee wages within a firm and assume it differs across firms only by its mean but not its shape. Under a higher minimum wage, the wage distribution becomes left-censored at the minimum wage and a certain share of workers are employed at the minimum wage itself and above marginal labor productivity. It follows that the more a firm's average wage w_s approaches the minimum wage $w^{\min}$, the larger the share of employees affected by any new minimum wage increase and the larger the increases in the firm's average wage without a commensurate increase in the "sticky" labor quality.[2] To capture this relationship between the average firm wage increase and a minimum wage hike, we can define an *impact function* (IF) as follows

$$IF(w_s/w^{\min}) = \frac{\Delta \ln w_s}{\Delta \ln w^{\min}} \quad \text{with} \quad IF' < 0. \tag{A4}$$

In the empirical part, we estimate the impact function using the functional form $IF(w_s/w^{\min}) = \lambda \left(w_s/w^{\min}\right)^{-(k+1)}$, where the parameter $\lambda > 0$ determines the strength of the average wage effect and $k > 0$ governs its convexity. Correctly characterizing the impact function allows for a better identification of the effective firm exposure to any given minimum wage increase.

The demand side of the model assumes a representative consumer with a utility function given in each period by

$$U = \left[C_L^{\frac{\theta-1}{\theta}} + C_H^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{A5}$$

subject to a period budget constraint $C_L p_L + C_H p_H = B$. We can normalize the price of good H as $p_H = 1$. The parameter $\theta > 1$ denotes the marginal rate of substitution. For $\theta \to \infty$, the two products become perfect substitutes and the market converges to the benchmark of perfect competition.

The model assumes a predetermined distribution of labor quality for each firm and ignores adjustment costs other than a limited (short-run) ability to replace low wage workers of low marginal

[1] Adjustment costs imply that substitution of a large share of the workforce (embodying Q) is neither feasible nor cost-effective in the short run.

[2] In the special case that the firm faces no frictions in firing all employees with labor productivity below the minimum wage and replace them with employees of higher quality, no competitive disadvantage results. But as convincingly argued by Long and Yang (2016), even Chinese private firms face considerable labor market rigidities in the short run.

labor productivity. The dynamic firm problem will generally differ from the myopic solution presented below. Firms could manage their labor pool dynamically in order to limit any future wedge between the expected minimum wage and the productivity of low-wage workers. But in practice, firms might find it hard to predict the evolution of the local minimum wage relative to the labor productivity growth for low wage workers. Dynamic consideration could therefore be of secondary importance and only attenuate the contemporaneous relationship derived for the myopic case in the next section.

A.2 Model Solution

Solving this simple neoclassical firm model with labor rigidity is straightforward. The consumer maximization problem for the utility function (A5) implies optimal consumption shares

$$C_L = \frac{1}{(p_L + p_L^{\theta})} B, \qquad C_H = \frac{p_L^{\theta}}{(p_L + p_L^{\theta})} B,$$

where $\theta > 1$ denotes the elasticity of substitution and we normalize the price of consumption good produced by the high wage firm to $p_H = 1$. Under market clearing with $Y_L = C_L$ and $Y_H = C_H$, we can write the product price p_L as a function of product output Y_L, namely

$$p_L = \left(\frac{Y_H}{Y_L} \right)^{\frac{1}{\theta}},$$

and the monopolistic firm value maximization problem implies four first-order conditions

$$\begin{array}{rr} p_L \alpha A_L K_L^{\alpha-1} (Q_L N_L)^{1-\alpha} = \frac{\theta}{\theta-1} r & \alpha A_H K_H^{\alpha-1} (Q_H N_H)^{1-\alpha} = \frac{\theta}{\theta-1} r \\ p_L (1-\alpha) A_L K_L^{\alpha} Q_L^{1-\alpha} N_L^{-\alpha} = \frac{\theta}{\theta-1} w_L & (1-\alpha) A_H K_H^{\alpha} Q_H^{1-\alpha} N_H^{-\alpha} = \frac{\theta}{\theta-1} w_H \end{array},$$

where the average labor quality corresponds to the average wage; that is $Q_L = w_L$ and $Q_H = w_H$. The equilibrium ratios of profit, output, capital, and labor follow as

$$\frac{\Pi_H}{\Pi_L} = \frac{Y_H p_H - rK_L - w_L L}{Y_L p_H - rK_H - w_H L} = \frac{\frac{1}{\theta} Y_H p_H}{\frac{1}{\theta} Y_L p_L} = \frac{Y_H p_H}{Y_L p_L} = \frac{K_H}{K_L} = \frac{L_H}{L_L} = \left(\frac{A_H}{A_L} \right)^{\theta - 1}.$$

The two firms differ in their average labor quality. If the labor input of each firm $s \in \{H, L\}$ has an average quality Q_s measured by the average firm wage w_s, we can write the quality-adjusted labor input as $L_s = w_s N_s$, where N_s denotes the number of employees. Minimum wage changes then have different effects on the average wage of each firm, while the average labor quality cannot adjust in the short run. Let the impact function IF characterize the effect of a minimum wage change $\Delta w^{\min}$ on the average wage of the firm such that

$$\Delta w_s = IF_s \ \Delta w^{\min}.$$

For a minimum wage change $\Delta w^{\min}$, the first-order conditions imply

$$\begin{aligned} p_L A_L \left(\frac{K_L}{L_L}\right)^{\alpha-1} &= A_H \left(\frac{K_H}{L_H}\right)^{\alpha-1} \\ p_L A_L \left(\frac{K_L}{L_L}\right)^{\alpha} \frac{1}{1+IF_L \Delta w^{\min}} &= A_H \left(\frac{K_H}{L_H}\right)^{\alpha} \frac{1}{1+IF_H \Delta w^{\min}}. \end{aligned}$$

For the equilibrium (value added) output, capital, and labor ratios we obtain

$$\begin{aligned} p_L &= \frac{A_H}{A_L}\left(\frac{1+IF_H\ \Delta w^{\min}}{1+IF_L\ \Delta w^{\min}}\right)^{\alpha-1} \\ \frac{Y_H p_H}{Y_L p_L} &= \frac{K_H}{K_L} = \frac{L_H}{L_L} = \frac{Q_H N_H}{Q_L N_L} = \left(\frac{A_H}{A_L}\left(\frac{1+IF_H\ \Delta w^{\min}}{1+IF_L\ \Delta w^{\min}}\right)^{1-\alpha}\right)^{\theta-1}. \end{aligned}$$

We can use the approximation

$$\ln \frac{1+IF_H\ \Delta w^{\min}}{1+IF_L\ \Delta w^{\min}} \approx (IF_H - IF_L) \ln \Delta w^{\min}$$

and express log change of any variable $\ln X$ from period 1 to period 2 as $\Delta \ln X = \ln X_t - \ln X_{t-1}$. If the minimum wage constraint is effective only in the second period after the shock $\Delta \ln w^{\min} > 0$, we obtain the following proposition:

> **Proposition 1: Optimal Adjustment of Capital to Labor Input Ratios**
>
> Assume two firms L and H with the Cobb-Douglas production function specified in equations (A1),(A2) and an asymmetric firm exposure of their average wage to a minimum wage change given by $IF_L > IF_H$, respectively. For a minimum wage change $\Delta \ln w^{\min}$, the profit maximizing adjustment of their relative capital to labor ratios follows as
>
> $$\Delta \ln \frac{K_L}{N_L} - \Delta \ln \frac{K_H}{N_H} = \Delta \ln w_L - \Delta \ln w_H \approx [IF_L - IF_H]\, \Delta \ln w^{\min}. \tag{A6}$$

According to Proposition 1, relative changes in the two-factor input ratios do not depend on any of the technology parameters of the Cobb-Douglas production functions α, β, or γ. We also highlight that the relative input ratios are invariant to any change in the productivity parameters $\Delta \ln A_L$ and $\Delta \ln A_H$ of firms L and H respectively. Neither does the relative factor ratio response of the two firms depend on the elasticity of substitution θ of their output and therefore on the degree of product competition. Only the relative exposure of the firm to the minimum wage change captured by the term $IF_L - IF_H$ matters for the optimal change in factor input ratios. All this suggests a simple reduced form regression with a firm's (log) capital share as the dependent variable and the interaction of a firm's exposure IF and the (log) minimum wage change $\Delta \ln w^{\min}$ as the explanatory variable. The results are reported in Table 3 of the paper.

But we also obtain closed form expressions for the other endogenous variables summarized as follows:

Proposition 2: Optimal Output and Factor Response

Faced with an increase in their average wage by $IF_L \times \Delta \ln w^{\min}$ and $IF_H \times \Delta \ln w^{\min}$ due to the minimum wage increase respectively, firms L and H optimally adjust their (relative) output (Y), capital input (K), employment input (N) and firm profits (Π) according to

$$\Delta \ln Y_L - \Delta \ln Y_H = -\theta \Delta \ln \frac{p_L}{p_H} \tag{A7}$$

$$\Delta \ln K_L - \Delta \ln K_H = -(\theta - 1) \Delta \ln \frac{p_L}{p_H} \tag{A8}$$

$$\Delta \ln N_L - \Delta \ln N_H = -(\theta - 1) \Delta \ln \frac{p_L}{p_H} - [IF_L - IF_H] \Delta \ln w^{\min} \tag{A9}$$

$$\Delta \ln \Pi_L - \Delta \ln \Pi_H = -(\theta - 1) \Delta \ln \frac{p_L}{p_H}, \tag{A10}$$

and where changes of the relative (log) output prices (p) follows as

$$\Delta \ln \frac{p_L}{p_H} = \Delta \ln A_H - \Delta \ln A_L + (1 - \alpha) [IF_L - IF_H] \Delta \ln w^{\min}. \tag{A11}$$

Proposition 2 highlights two distinct channels through which the minimum wage shock affects relative firm outputs, factor inputs and firm profits. The relative employment change $\Delta \ln N_L - \Delta \ln N_H$ in Eq. (A9) is inversely proportional to the respective relative increase of the average wage given by $[IF_L - IF_H] \Delta \ln w^{\min}$. A second effect concerns the role of the minimum wage change for the competitive position of each firm captured by the change in relative product prices $\Delta \ln \frac{p_L}{p_H}$. Optimal monopolistic output pricing implies an adjustment of the relative product prices in proportion to (i) the product of the labor share $(1-\alpha)$ and exogenous relative average wage increase $[IF_L - IF_H] \Delta \ln w^{\min}$ and (ii) the relative changes $\Delta \ln A_H - \Delta \ln A_L$ in firm productivity. In the absence of any endogenous productivity response to changing labor costs, the competitive effect on relative output and all factor inputs simplifies to the single term $-(\theta-1) \Delta \ln \frac{p_L}{p_H}$ in Eq. (A9). The larger the product price increase of firm L relative to firm H, the larger the loss in market share of the low-wage firm becomes. More product market competition, represented by a higher θ, aggravates the relative production decrease of low-wage firm L.

These results highlight the role of heterogeneous exposure under minimum wage changes and motivate the regressions reported in Table 4. Low wage firms suffer a negative competitive shock in proportion to the relative average wage changes $[IF_L - IF_H] \Delta \ln w^{\min}$. Neoclassical investment theory under employment rigidities predicts a relative decrease in firm output and capital input given by $-(\theta-1)(1-\alpha) [IF_L - IF_H] \Delta w^{\min}$. The relative employment decrease is predicted to be even larger at $-[1 + (\theta - 1)] (1 - \alpha) [IF_L - IF_H] \Delta w^{\min}$. Next we show how these results are partly overturned under an endogenous productivity response by low-wage firms.

A.3 Endogenous Productivity Response and its Channels

Propositions 1 and 2 characterize the optimal firm response under exogenous relative factor productivity, that is $\Delta \ln A_H - \Delta \ln A_L$ itself does not respond to the minimum wage shock. Yet a minimum wage shock could trigger an endogenous firm response that changes the (relative) total factor productivity of the low-wage firm.

We distinguish two theories that can rationalize such a differential productivity effect under adverse competitive shocks. First, the *theory of efficiency wages* assumes that high wages can increase labor productivity because higher pay can mobilize a higher level of labor productivity in a way that the labor contract itself cannot. Higher wages increase any potential employee loss related to contract termination and as a consequence, the opportunity cost of shirking increases. It might also reduce the cost of labor turnover which tends to be high among low skill manufacturing workers. Positive productivity effects of minimum wage increases rely on an inefficiently low prior wage and represent an improvement in labor productivity at the bottom of the organizational hierarchy. Importantly, such productivity gains should be available independently of a firm's governance, and should not be contingent on firm ownership.

Second, an endogenous response could result from *managerial incentives* if private payoffs of managers are a concave function of *relative* changes in firm profitability. Performance monitoring mechanisms can benchmark the firm performance against that of the competitor and sanction relative underperformance, for example, with an increased likelihood of firing the CEO or the top management team. A large literature on managerial incentives has discussed the important role of *relative performance evaluations* (RPE). Optimal contract design seeks to maximize the signal to noise ratio, and this translates into a negative (positive) weight on the performance of industry peers in the optimal incentive pay (non-retention) decision (Holmström, 1982). Jayaraman *et. al.* (2018) find strong evidence for RPE in US corporate CEO pay and firing practices. For firms with a large peer group, common industries-wide shocks are easy to identify, and are fully filtered out in the performance evaluation as the RPE paradigm suggests. For a more extensive survey of the literature on executive compensation and retention, we refer to Edmans, Gabaix and Jenter (2017). Their recent summary article also refers to an incentive theory that focuses on punishment for underperformance as we do in our model (see in particular the chapter on Executive Turnover).

We assume that the manager's utility in the low-wage and high-wage firms is represented by the functions

$$\begin{aligned} U_L &= \gamma \min(\Delta \ln \Pi_L - \Delta \ln \Pi_H, 0) - \frac{1}{2} (\Delta \ln A_L)^2 \\ U_H &= \gamma \min(\Delta \ln \Pi_H - \Delta \ln \Pi_L, 0) - \frac{1}{2} (\Delta \ln A_H)^2 , \end{aligned} \tag{A12}$$

respectively, where $\Delta \ln \Pi_L - \Delta \ln \Pi_H$ denotes the change in the (log) profit difference between the two firms and $\gamma \min(\Delta \ln \Pi_L - \Delta \ln \Pi_H, 0)$ the manager's punishment for relative underperformance (in terms of relative profitability) in the low-wage firm. Let $\gamma > 0$ represent a utility parameter for the strength of punishment for relative underperformance. The second term $\frac{1}{2}(\Delta \ln A_s)^2$ ($s = L, H$) denotes the quadratic utility loss from exerting managerial effort in order to achieve a positive productivity increase $\Delta \ln A_s \geq 0$. This allows us to interpret the TFP improvement $\Delta \ln A_s$ as the private effort of the manager. Private (non-contractable) managerial effort introduces a governance frictions into the model.

Next, we determine the Nash equilibrium $(\Delta \ln A_L^*, \Delta \ln A_H^*)$ in managerial effort (and TFP increases) in both firms for a positive minimum wage shock $\Delta w^{\min} > 0$. The relative (log) profit change follows from Eqs. (A10) and (A11) as

$$\Delta \ln \Pi_L - \Delta \ln \Pi_H = (\theta - 1)\left[\Delta \ln A_L - \Delta \ln A_H\right] - (\theta - 1)(1 - \alpha)\left[IF_L - IF_H\right] \Delta \ln w^{\min}. \quad \text{(A13)}$$

The optimal effort level of the manager in the low wage firm (for $\Delta \ln \Pi_L - \Delta \ln \Pi_H < 0$) is given by the first-order condition

$$\frac{d}{d(\Delta \ln A_L)} \gamma \left(\Delta \ln \Pi_L - \Delta \ln \Pi_H\right) = \Delta \ln A_L^* \quad \Rightarrow \quad \gamma(\theta - 1) = \Delta \ln A_L^*.$$

The optimal effort of the manager in the high-wage firm is zero, $\Delta \ln A_H^* = 0$, because this maximizes his utility at $U_H = 0$ if $\Delta \ln \Pi_H - \Delta \ln \Pi_L \geq 0$. The Nash equilibrium in the endogenous TFP response follows as

$$\Delta \ln A_L^* = \min\left\{\gamma(\theta - 1), \Delta\overline{\ln A}_L\right\} > 0 \quad \text{and} \quad \Delta \ln A_H^* = 0, \quad \text{(A15)}$$

where $\Delta\overline{\ln A}_L \geq 0$ denotes the maximum productivity increase of the low-wage firm when $\Delta \ln \Pi_L = \Delta \ln \Pi_H$. Exerting effort beyond profit growth equalization is never optimal for the manager in the low-wage firm. Moreover, $\Delta \ln \Pi_L = \Delta \ln \Pi_H$ implies for the maximal TFP response of the low-wage firm

$$\Delta\overline{\ln A}_L = (1 - \alpha)\left[IF_L - IF_H\right] \Delta \ln w^{\min} > 0.$$

Hence, the low-wage firms compensates its relative profit growth shortfall only partially (and not fully) if

$$0 < \gamma < \frac{1 - \alpha}{\theta - 1}\left[IF_L - IF_H\right] \Delta \ln w^{\min}.$$

This example illustrates how management in the low-wage firm responds endogenously to a relative profit shortfall after the minimum wage shock if corporate governance sanctions a relative performance shortfall as stated in Eq. (A12). The manager in the high-wage firm does not increase productivity as he do not face any punishment for underperformance. Generally, performance monitoring relative to industry peers should generate a stronger endogenous response of the low wage firms as summarized in the following proposition:

Proposition 3: Managerial Incentives and the Endogenous TFP Response

Under managerial slack and a firm management sanctioned for a performance shortfall *relative* to industry peers as stated in Eq. (A12), a minimum wage hike should increases total factor productivity more in the low-wage firm (L) than an industry peer with higher wages (H), that is

$$\begin{aligned} \Delta \ln A_L^* &= \min\left\{\gamma(\theta - 1), \Delta\overline{\ln A}_L\right\} > 0 \quad \text{(A16)} \\ \Delta \ln A_H^* &= 0. \end{aligned}$$

The endogenous productivity response by low-wage firms to adverse minimum wage shocks will lower the output and factor input reduction predicted in Proposition 2. Depending on the magnitude of the productivity response embodied in the parameter $\gamma > 0$, the optimal relative product price change decreases to

$$\Delta \ln \frac{p_L}{p_H} = (1-\alpha) \left[IF_L - IF_H \right] \Delta \ln w^{\min} - \min \left\{ \gamma \left(\theta - 1 \right), \Delta \overline{\ln A}_L \right\} > 0. \tag{A17}$$

Under a strong endogenous productivity response by low-wage firms to adverse minimum wage shocks, their product output, factor inputs and firm profitability can keep up with that of the high wage firm, provided that $\gamma \left(\theta - 1 \right) \geq \Delta \overline{\ln A}_L$.

Importantly, relative performance incentives embodied in the parameter γ are likely to be stronger in firms with better monitoring practise, better target setting practise and more merit based evaluations, —namely the three dimensions of management practise surveyed by Bloom and van Reenen (2007, 2010). This can explain why the management quality is correlated with the endogenous productivity under minimum wage hikes as shown in Table 6. In order to obtain a differential productivity responses of low wage firms by ownership type as found in Table 5, we need to assume that SOEs have on average weaker incentives, namely

$$\gamma_{SOE} < \gamma_{private} < \gamma_{foreign}. \tag{A18}$$

This implies for the strength of the endogenous productivity response of low wage firm

$$(\Delta \ln A_L^*)_{SOE} \leq (\Delta \ln A_L^*)_{private} \leq (\Delta \ln A_L^*)_{foreign}, \tag{A19}$$

whereas $\Delta \ln A_H^* = 0$ for all three ownership types. This rationalizes the results obtained in Table 5.

B. Sample Construction

Our data source is the Annual Survey of Industrial Firms during the period 1998–2008. The survey reports on industrial firms from the mining, manufacturing, and public utility sectors. This section describes the data-cleaning and filtering procedure used for obtaining the sample used in the analysis.

B.1 Data Cleaning

The raw data comprise 2,615,016 firm-year observations, corresponding to 666,554 distinct firms. We apply consecutively the following data-cleaning operations:

1. We drop firm-year observations with missing, zero, or negative values for total assets, output, book value of fixed assets, operating revenues, and employment. In addition, we drop firm-year observations for which operating status are not reported as "normal". This implies dropping 105,476 firm-year observations (or 4%).
2. We drop firm-year observations with fewer than eight employees.
3. We drop firm-year observations with revenue (sales) or output lower than 10,000 Yuan or revenues per employee or output per employee lower than 1,000 Yuan.
4. We drop firms that do not report a correct location code for every firm-year.

The gross sample has 2,442,439 firm-year observations, corresponding to 619,877 distinct firms.

B.2 Data Filtering

Next, we apply a series of data filters that exclude firm-year observations outside a reasonable range of variable variation. Such observations are likely to represent reporting errors or just extreme firm events discarded from the sample. The following filters are applied sequentially:

1. For every observation in our regressions, we require that the corresponding (one-year) lagged observation exists. A missing lagged observation implies that the contemporaneous observation is not used in the analysis. In total 668,147 firm-year observations are thus excluded.
2. We exclude firm-year observations for which the real minimum wage changes feature extreme negative correlation for two consecutive years, namely if $\Delta w_t^{\min} \times \Delta w_{t-1}^{\min} < -0.04$. This accounts for 3,540 discarded firm-year observations.
3. We exclude 486,403 firm-year observations if certain critical variables are below the 1% quantile or above the 99% quantile of its annual distribution. These critical variable are the following:
   (a) The ratio of the local minimum wage to the firm wage, where firm wage is defined as the average employee wage.

(b) Firm wage growth demeaned by firm wage growth at the city level.

(c) The growth rate of output per employee, capital stock per employee, and intermediate input per employee, all demeaned at the city level.

(d) The growth rate of firm value-added, firm capital, firm employment, and firm TFP $A1$, all demeaned at the city level.

4. As minimum wage legislation became more stringently enforced in the later years of the sample, we focus most of our analysis on the period 2002-08. Data for the years 2000-01 only enters as lagged dependent and instrumental variable data.

The final sample for our regressions has 1,190,070 firm-year observations for the period 2002-08, corresponding to 365,813 different firms.

B.3 Summary Statistics

We divide firms into three size groups according to the number of employees. Small firms have 8-200 employees, medium-size firms 201-1,000 employees and large firms more than 1,000 employees. The number of firms covered increases over time. The exception here is the year 2008, for which value added is not directly reported. Instead we have to infer value added in 2008 using the reported operating costs, which results more frequently in missing values. Table A1 reports summary statistics on the number of firms by size, aggregate employment and output. Additional summary statistics on each variable are reported in Table 1 of the paper. The sample coverage of small firms is particularly incomplete in the early period 2002-04.

B.4 Productivity Measurement Based on Cost Shares

Here we describe the construction of the four different measures of total factor productivity (TFP). The firm (net) output measure used in the analysis is value added defined as the difference between (deflated) gross revenue and the (deflated) value of the intermediary good inputs; formally

$$Y = \textit{Gross Revenue}/p_Y - \ \textit{Cost Intermediary Goods}/p_X, \tag{B1}$$

where p_Y and p_X denote the industry output price index and the intermediary good price index, respectively. Total (log) total factor productivity (TFP) growth is defined as the change in the difference between log net output value and the value of labor input and capital costs at constant lagged firm wages $w_{s,t-1}$ and constant lagged factor shares α_L and α_K,

$$\Delta \ln A_{s,t} = \ln A_{s,t} - \ln A_{s,t-1} = \ln Y_{s,t} - \ln Y_{s,t-1} - \alpha_L (\ln w_{s,t-1} N_t - \ln w_{s,t-1} N_{s,t-1}) - \alpha_K (\ln K_{s,t} - \ln K_{s,t-1}).$$

This implies that TFP growth is measured in terms of labor and capital input and not affected by contemporaneous changes in firm wages. We assume that the labor and capital share of production,

α_L and α_K, respectively, add up to 1. Cost minimization implies that the optimal factor inputs correspond to the labor and capital share of production. We use a wage-based labor input measure, but apply lagged firm wages $w_{s,t-1}$ to exclude any effect of contemporaneous wages on the calculation of the labor share. Formally, the labor and capital shares follow as

$$\alpha_L(s,t) = \frac{w_{s,t-1}N_{s,t}}{w_{s,t-1}N_{s,t} + (r_s + \delta_s)K_{s,t}} \quad \text{and} \quad \alpha_K(s,t) = \frac{(r_s + \delta_{s,t})K_{s.t}}{w_{s.t-1}N_{s,t} + (r_s + \delta_{s,t})K_{s,t}}, \tag{B2}$$

respectively. For the cost of capital we use an interest rate of $r_s = 7\%$ for all large firms, $r_s = 7.7\%$ for medium size firms, and $r_s = 8.4\%$ for small firms.[3] Added to the capital costs is capital depreciation $\delta_{s,t}$ inferred from the yearly accounting depreciation of each firm.

Next we define the four different TFP growth measures ($n = 0, 1, 2, 3$)

$$\Delta \ln An_{s,t} = \ln Y_{s,t} - \ln Y_{s,t-1} - \widehat{\alpha}_L^n(\ln w_{s,t-1}N_{s,t} - \ln w_{s,t-1}N_{s,t-1}) - (1 - \widehat{\alpha}_L^n)(\ln K_{s,t} - \ln K_{s,t-1}). \tag{B3}$$

These differ in their use of the particular labor shared used. The first total productivity measure $\ln A0$ is based on productivity parameter $\widehat{\alpha}_L^0$ equal to the firm- and year-specific labor share $\alpha_L(i,t)$; therefore

$$\widehat{\alpha}_L^0 = \alpha_L(s,t). \tag{B4}$$

This measure allows for firm- and time-specific variation of the labor share. The second total total factor productivity measure $\ln A1$ is based on a productivity parameter $\widehat{\alpha}_L^0$ averaging all time observations $T(s)$ available for a firm s; that is

$$\widehat{\alpha}_L^1 = \frac{1}{\sharp T(s)} \sum_{t \in T(s)} \alpha_L(s,t). \tag{B5}$$

This measure of total factor productivity should give good results if the optimal labor share of a firm is reasonably constant over time. The third total productivity measure $\ln A2$ does not assume such time invariance, but instead averages the labor share of production of all firms $I(s)$ in the same industry as firm s; therefore

$$\widehat{\alpha}_L^2 = \frac{1}{\sharp I(s)} \sum_{i \in I(s)} \alpha_L(s,t). \tag{B6}$$

The quality of this measure depends on the industry homogeneity with respect to the labor share. The fourth total productivity measure $\ln A3$ is based on a labor share estimate that minimizes the time and cross-sectional variation of $\alpha_L(s,t)$. We undertake a panel regression

$$\alpha_L(s,t) = \gamma_0 + \gamma_T D_T + \gamma_I D_I + \epsilon \tag{B7}$$

using matrices of firm dummies D_{Firm} and interacted industry and year dummies $D_{Ind \times Year}$ as re-

[3] The interest rate of 7% was the benchmark (minimum) corporate bank loan rate during the period of 2002–08 and could increase to a maximum of 8.4%. We assume that small size firms paid the maximum rate and medium size firms a rate between the minimum and the maximum. Variations in these assumptions do not qualitatively change any of the results.

gressors and define

$$\widehat{\alpha}_L^3 = \widehat{\gamma}_0 + \widehat{\gamma}_1 D_{Firm} + \widehat{\gamma}_2 D_{Ind\times Year}. \tag{B8}$$

The last measure generalizes the previous two in the sense that $\widehat{\alpha}_L^3 = \widehat{\alpha}_L^1$ if we impose the restriction $\gamma_2 = 0$ and $\widehat{\alpha}_L^3 = \widehat{\alpha}_L^2$ if we impose the restriction $\gamma_1 = 0$.

B.5 Productivity Measurement Based on Proxy Methods

Following the work of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015), estimation of output elasticities can be refined by using observed variation in investment or intermediate inputs as proxies for unobserved firm productivity changes. Based on certain regularity conditions and assumptions on a firm's input dynamics, the proxy approach estimates the unobserved firm productivity non-parametrically.

Both the LP and ACF method are available as STATA routines and we implement them as an alternative to the cost share methods described in Section B.4. The STATA commands applied are `levpet` and `acfest` for the LP and ACF method, respectively. The obtained output elasticities are reported in Table A8 and depicted in Figure 1 of the Appendix. Both the LP and the ACF method produce lower and more volatile output elasticities for the labor input compared to the cost share method. However, the implications for changes in log TFP are negligible: Those obtained by the cost share method ($\Delta \ln A1$) shows a correlation of 0.955 and 0.973 with those of the LP and ACF method, respectively.

C. Robustness Considerations

This section explores the stability of our results in three dimensions. First, we verify in Section C.1 that alternative inferences about the productivity parameters α_L and α_K of the production function confirm the results described in the previous section. In Section C.2 we discuss if TFP mismeasurement could be specific to the firm and ownership type. A third robustness check in Section C.3 concerns the pattern of firm exit, which is shown not to coincide with the productivity surge observed in the year of the minimum wage increase.

C.1 Alternative Productivity Measures

In Section 6.3 of the paper, we calculate TFP growth using productivity parameters α_L and α_K derived from a firm's average factor cost share of labor and capital, respectively. While this inference does not impose any common productivity structure across firms in the same industry, it ignores any intertemporal change in the factor shares. An alternative approach is to assume common productivity parameters within an industry, but variability across time: Our second measure of TFP growth $\Delta \ln A2_{s,t}$ is therefore based on the intra-industry average of $\alpha_{L/K}(s,t)$ for all firm observations within a given industry and year.

We repeat the regression results in Table 5 using this alternative TFP measure and find quantitatively similar results. For example, the point estimate for the interaction term $IF_s \times \Delta \ln w^{\min} \times D\_foreign$ in Table 5, Columns (4) changes from 0.655 to 0.676 with almost the same standard errors.[4] This suggests that our inference about TFP growth is not sensitive to the assumed time invariance of the firm parameters α_L and α_K.

A third and more general inference about the productivity parameters α_L and α_K consists of a panel regression of the firm-year observations $\alpha_{L/K}(s,t)$ on both firm and interacted industry and time fixed effects. The predicted value $\widehat{\alpha}_{L/K}(s,t)$ then represents a combination of time and cross-sectional intra-industry averaging of cost shares. The corresponding third measure of TFP growth $\Delta \ln A3_{s,t}$ again yields quantitatively similar results that associate adverse labor cost shocks with higher TFP growth.

Firm output can also be influenced by latent variables which do not enter the input measurement. Levinsohn and Petrin (2003) propose the use of other intermediate inputs in order to estimate such unobservable output contributions. This can improve the estimation of productivity parameters if these intermediate inputs are not themselves subject to measurement error. Ackerberg, Caves, and Frazer (2015) propose a further generalization. We implement both methods as a robustness check in the Internet Appendix, where Table A10 compares the coefficient estimates for each industry across three methods. Panel A and B of Table A11 replicate the baseline regressions of Table 5 for TFP measures obtained by the LP and ACF method, respectively. Both the LP and ACF method produce a much larger variation for the industry specific parameters α_L and α_K compared to the cost share method. Some coefficients are implausibly low or high, which suggests that the LP and ACF methods are not robust enough for our data sample. In spite of this sensitivity of the production parameters,

[4] We report these results in Table A6 of the Internet Appendix.

all the qualitative results of Table 5 are robust to these alternative TFP measurement methods. We can explain this robustness by the fact that much of the productivity surge around minimum wage increases is accounted for by output increases and the inferred TFP change is rather insensitive to the estimated production coefficients. Indeed, changes in log TFP for the cost share method show a correlation of 0.960 and 0.979 with those of the LP and ACF method, respectively.

Time-varying unobservable input variations cannot be excluded as a contribution to the measured output increases and may overestimate the productivity gain under minimum wage shocks. But industry-wide fluctuations of capacity use and inventory are presumably captured by interacted industry and time fixed effects. And if unobservable input factors play a similar role for SOEs and private firms, the conclusion about the relatively stronger productivity increase in the private sector should be robust.[5]

C.1 Ownership Specific TFP Mismeasurement

Measurement biases with respect to TFP plausibly differ across firm ownership types. However, any constant (or constantly growing) measurement bias is absorbed through differencing of the dependent variable and the inclusion of firm fixed effects. For a TFP measurement bias to affect our inference, it needs to correlate with the minimum wage increase and a firm's exposure to the minimum wage shock. Any such exogenous correlation is rather unlikely. Yet, the production response of the firm to the minimum wage change can give rise to endogenous measurement errors correlated with minimum wage changes and firm exposure. For example if a firm's scale economies differ from constant return to scale (as assumed by the cost share method) by a factor $1-\beta$, we can calibrate the TFP measurement error as

$$\Delta \ln \widehat{A} - \Delta \ln A = -[\alpha \Delta \ln L + (1-\alpha)\Delta \ln K](1-\beta). \tag{2}$$

According to Table 4, the endogenous input response to minimum wage shocks $IF_s \times \Delta \ln w^{\min}$ follows for labor $\Delta \ln L$ and capital $\Delta \ln K$ as -0.195 and 0.156, respectively. For $\alpha = 2/3$, the resulting TFP measurement bias is quantified as

$$\Delta \ln \hat{A} - \Delta \ln A = 0.0777(1-\beta) \times IF_s \times \Delta \ln w^{\min}. \tag{3}$$

For example, a mismeasurement of scale economies by $1-\beta = 0.2$ implies a bias for the key coefficient of interest (i.e. $IF_s \times \Delta \ln w^{\min} \times D\_x$) in Table 5 of only 0.0156. But this amounts to only 2% (= 0.0156/0.655) of the estimate coefficient for foreign-owned firms. Any incorrect inference of scale economies across different ownership types cannot account for the quantitatively large differences in the endogenous productivity response.

Another concern about productivity comparisons between SOEs and private sector firms is that the former operated with redundant workers not productively employed. During the period 2002-2006, the labor share of SOEs continues to converge to the labor share of private firms [Hsieh and Song

[5] In particular, labor market practices of SOEs and private firms with respect to firing redundant workers had already converged by 2002 at the start of our sample period (Cai, Park and Zhao; 2008).

(2015), Figure 10]. Any reduction in surplus labor should imply a positive contribution to measured TFP. Yet, there is no evidence that the labor input reductions of SOEs coincide with minimum wage increases as shown by the insignificant coefficient for the term $IF_s \times \Delta \ln w^{\min} \times D\_SOE$ in Table 4, Column (5). Any gradual decrease of a redundant workforce in SOEs should augment TFP trend growth and is absorbed by firm fixed effects.

We also check if data reporting quality systematically varies by firm ownership type. To do so, we measure the percentage of reported data entries for output value, intermediate input value, and value added output that violate the respective accounting identify. The percentage of inconsistent observations for SOEs is at 1.05% almost identical to 1.03% in the full sample of all firms. Hence, firm-type differences in reporting quality are unlikely to generate a substantial attenuation bias for the endogenous productivity response of SOEs relative to foreign- or private-owned firms.

C.3 Firm Exit

The unbalanced nature of our firm sample suggests that low-productivity firms exit the market. If firms operate below capacity or at an inefficient scale, firm exit should increase output and augment the productivity of the remaining manufacturers. But such exit induced demand externalities can only account for the observed productivity surge if firm exit also coincides with the year and location of the minimum wage increase.

To explore this channel, we flag firm-years with a dummy variable $Exit_{s,t} = 1$ (and zero otherwise) if firm s reports in years $t-2$ and $t-1$ and stops reporting in year t and all consecutive years. Approximately 10% of firms feature such reporting discontinuities (indicative of market exit) in any year from 2004 to 2007. We define two additional dummies $D_{s,t}^{P50}$ and $D_{s,t}^{P90}$ which mark firm-years in which the minimum wage change exceeds either the 50% quantile ($\Delta \ln w^{\min} > 0.102$) or the 90% quantile ($\Delta \ln w^{\min} > 0.211$) of minimum wage changes experienced by all firms.

The correlation (Spearman's rho) between $Exit_{s,t}$ and $D_{s,t}^{P50}$ (or $D_{s,t}^{P90}$) is positive and extremely low at 0.0042 (or 0.0083). The hypothesis of statistical independence cannot be rejected in spite of the large sample size. This result does not imply that minimum wage changes are without consequences for firm exit in the long run—nor that such firm exit has no positive demand externalities. But if firm exit coincides with reporting discontinuities, it is not clustered in firm-years in which large minimum wage increases occur. Hence, firm exit and the corresponding demand externalities cannot account for the fact that productivity increases coincide with minimum wage shocks. In addition, it is unclear why firm exit would boost output and productivity just among private-owned and foreign-owned firms, but not among SOEs. We therefore discard the hypothesis that the positive TFP effect is related to market exit.[6]

[6] In a related paper, Mayneris, Poncet, and Zhang (2018) suggest that minimum wage increases in China trigger exit by less productive firms. We run additional probit regression for firm survival until 2008 based on the Chinese Economic Census available for this year, but do not find robust evidence that prior minimum wage shocks directly increase the probability of market exit.

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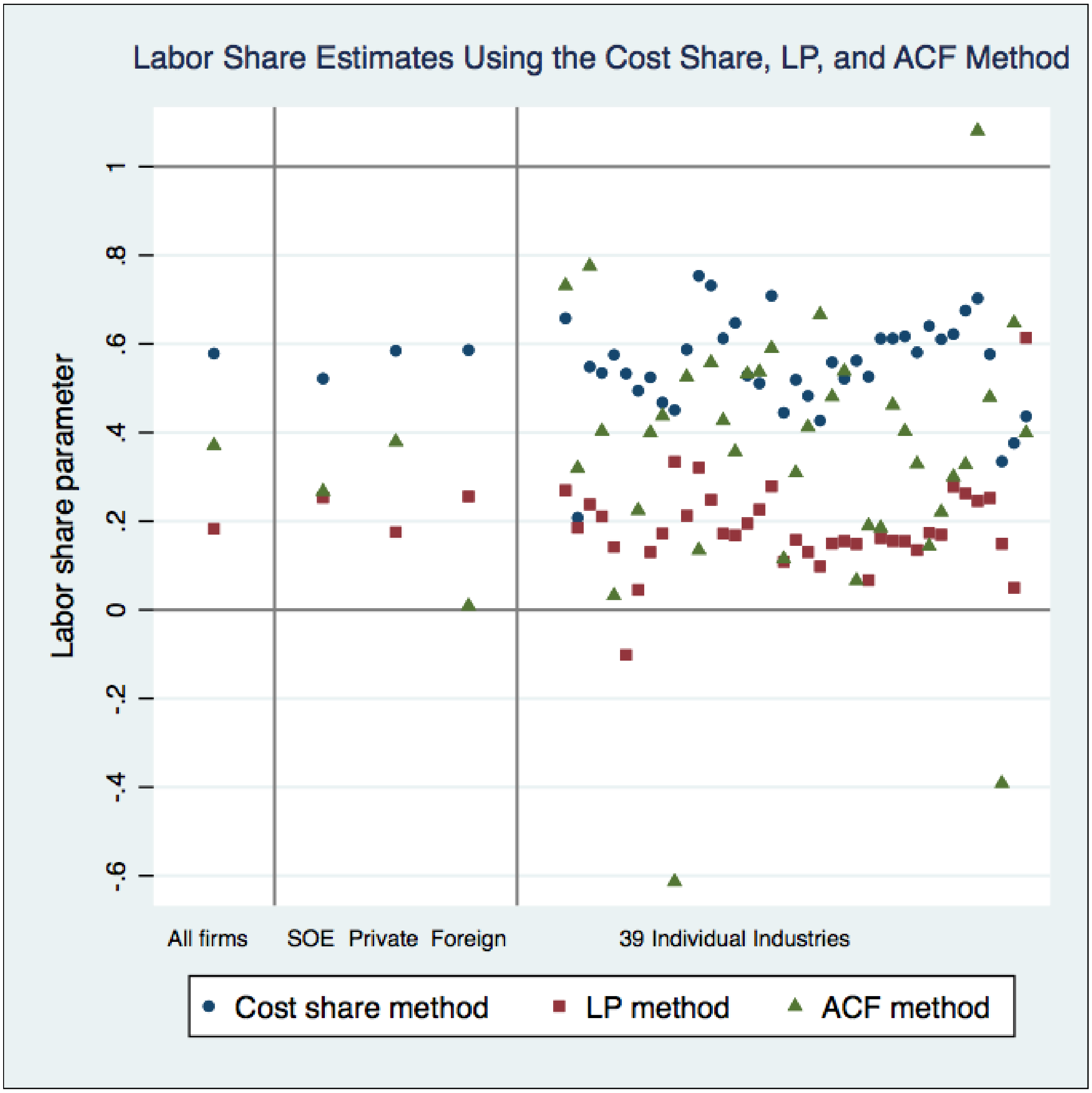

Figure 1: The graph compares labor share estimates by industry obtained under the cost share method (assuming $\alpha_L + \alpha_K = 1$), the LP method (Levinsohn and Petrin, 2003) and the ACF method (Ackerberg, Caves, and Frazer, 2015).

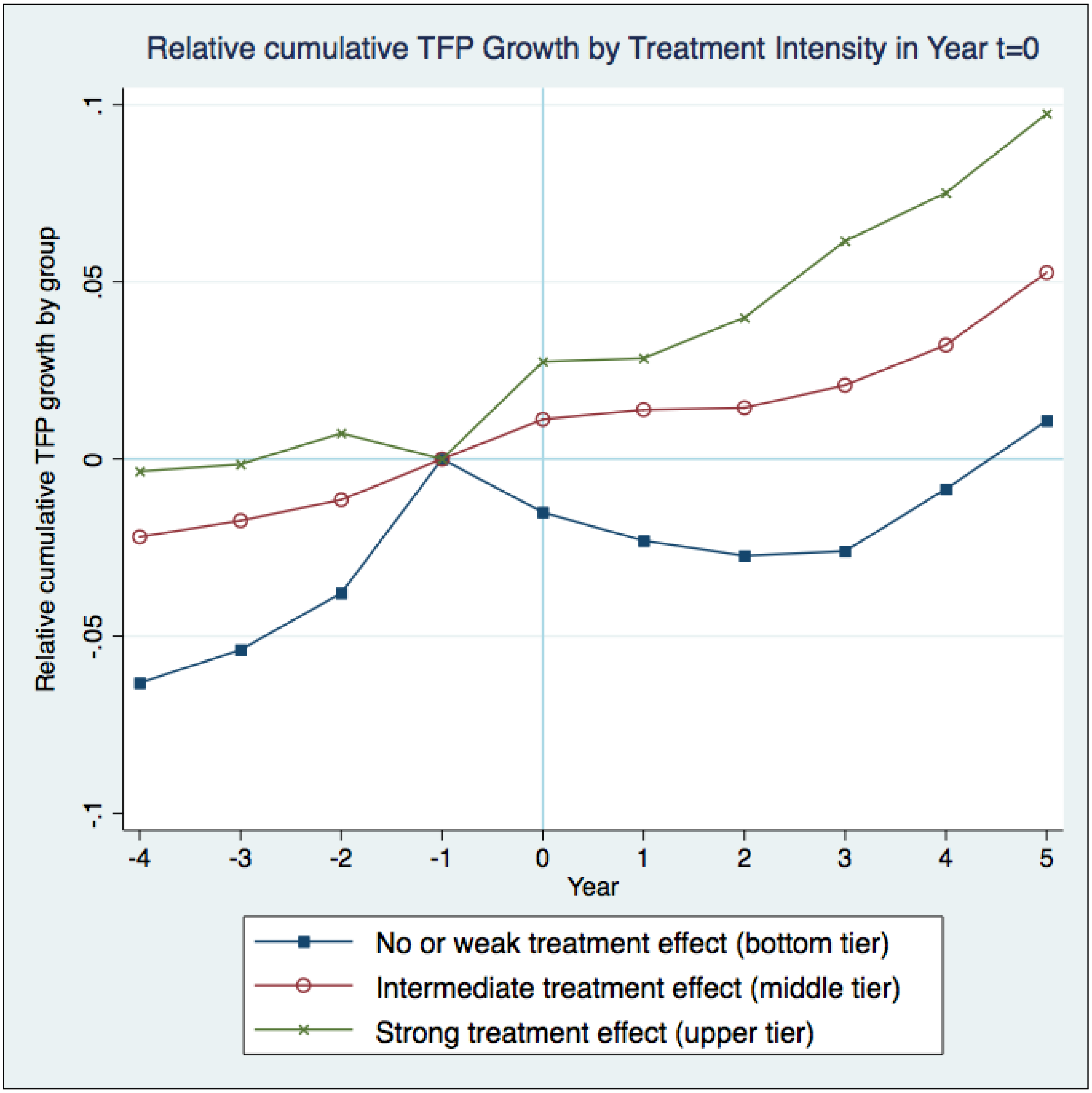

Figure 2: Firms are sorted by the intensity of treatment ($IF_s \times \Delta \ln w^{\min}$) in year $t = 0$ into three firm groups with (i) no or weak treatment (bottom tier), (ii) intermediate treatment (middle tier), and (ii) strong treatment. We plot the (unexplained) cumulative average growth from $t = -3$ to $t = 5$ of each firm group after subtracting firm-specific average growth rates over the entire period. The sequencing of minimum wage increases implies that the likelihood of no treatment in $t = 0$ correlates with a higher likelihood of treatment in $t - 1$.

Table A1: Sample Observations and Coverage of the Industrial Sector

Our data source is the Annual Survey of Industrial Firms during the period 1998–2008. After the data cleaning procedure described in Appendix B, the final sample comprises 1,201,803 firm-year observations for the period 2002-2008, and 370,458 different firms. We divide firms into three size groups according to the number of employees. Small firms have 8-200 employees, medium-size firms 201-1,000 employees and large firms more than 1,000 employees. We report aggregate statistics for employment in Column (5) and output in Column (6).

Year	Firm Observations				Sample Aggregates	
	Small	Medium	Large	All	Employment	Output (Million Yuan)
	(1)	(2)	(3)	(4)	(5)	(6)
2002	70,749	35,375	6,669	112,793	41,010,491	8,303,669,650
2003	78,208	37,487	6,801	122,496	42,725,667	10,260,656,565
2004	82,299	37,565	6,572	126,436	42,064,216	12,561,409,976
2005	135,863	48,740	7,624	192,227	53,128,158	17,961,341,645
2006	144,432	51,777	8,254	204,463	57,730,659	23,307,605,310
2007	163,605	55,810	8,685	228,100	61,748,755	30,290,618,247
2008	156,755	50,755	7,778	215,288	55,559,026	31,326,450,779

Table A2: Summary Statistics across Ownership Types

Panel A describes the firm characteristics for state-owned enterprises (SOEs), Panel B for private-owned Chinese firms, and Panel C for foreign-owned firms. For each firm sample, we report (annual) changes in the (log) capital to labor ratio $\Delta \ln(K/N)$, changes in the (log) (value added) output $\Delta \ln(Y)$, changes in (log) labor input $\Delta \ln(N)$, changes in the (log) capital stock $\Delta \ln(K)$, and changes with respect to two measures of total factor productivity $\Delta \ln(A1)$ and $\Delta \ln(A2)$. The impact function IF_s characterizes a firm's exposure to minimum wage changes.

	Obs.	Mean	STD	Skew.	Kurt.	P10	P50	P90
Panel A: State-owned enterprises (SOEs)								
$\Delta \ln(K/N)$	113,291	0.052	0.379	1.094	8.469	−0.262	−0.013	0.473
$\Delta \ln(Y)$	113,291	0.080	0.659	−0.093	4.380	−0.713	0.090	0.845
$\Delta \ln(N)$	113,291	−0.024	0.239	−0.187	9.366	−0.246	−0.004	0.177
$\Delta \ln(K)$	113,291	0.028	0.330	1.933	13.220	−0.139	−0.056	0.347
$\Delta \ln(A1)$	113,291	0.077	0.666	−0.099	4.223	−0.736	0.094	0.856
$\Delta \ln(A2)$	113,291	0.078	0.665	−0.090	4.226	−0.732	0.094	0.857
$IF_s \times \Delta \ln w^{\min}$	113,291	0.028	0.046	8.270	141.800	0.000	0.016	0.064
$\Delta \ln w^{\min}$	113,291	0.105	0.085	0.877	3.700	0.000	0.092	0.227
IF_s	113,291	0.288	0.342	5.478	49.208	0.071	0.197	0.558
$w_s/w^{\min}$	113,291	3.850	2.463	1.953	9.506	1.511	3.263	6.907
Panel B: Private-owned Chinese firms								
$\Delta \ln(K/N)$	829,110	0.106	0.505	0.830	5.836	−0.392	0.023	0.723
$\Delta \ln(Y)$	829,110	0.186	0.624	−0.086	4.468	−0.546	0.185	0.925
$\Delta \ln(N)$	829,110	0.031	0.309	0.321	6.032	−0.288	0.000	0.391
$\Delta \ln(K)$	829,110	0.137	0.458	1.519	7.999	−0.135	0.002	0.691
$\Delta \ln(A1)$	829,110	0.107	0.630	−0.143	4.262	−0.654	0.120	0.851
$\Delta \ln(A2)$	829,110	0.111	0.626	−0.124	4.266	−0.643	0.120	0.853
$IF_s \times \Delta \ln w^{\min}$	829,110	0.042	0.041	4.462	68.692	0.005	0.034	0.086
$\Delta \ln w^{\min}$	829,110	0.112	0.074	0.757	3.966	0.018	0.108	0.217
IF_s	829,110	0.387	0.264	4.438	47.335	0.149	0.341	0.651
$w_s/w^{\min}$	829,110	2.705	1.646	3.659	28.230	1.400	2.289	4.386
Panel C: Foreign-owned firms								
$\Delta \ln(K/N)$	259,402	0.054	0.433	0.994	7.186	−0.359	−0.007	0.549
$\Delta \ln(Y)$	259,402	0.148	0.648	−0.035	4.273	−0.616	0.146	0.923
$\Delta \ln(N)$	259,402	0.036	0.298	0.200	5.885	−0.275	0.000	0.375
$\Delta \ln(K)$	259,402	0.090	0.374	1.961	11.529	−0.102	−0.017	0.486
$\Delta \ln(A1)$	259,402	0.092	0.638	−0.070	4.201	−0.670	0.096	0.854
$\Delta \ln(A2)$	259,402	0.093	0.635	−0.059	4.201	−0.664	0.095	0.852
$IF_s \times \Delta \ln w^{\min}$	259,402	0.032	0.033	4.418	83.188	0.004	0.024	0.068
$\Delta \ln w^{\min}$	259,402	0.105	0.064	0.498	4.047	0.023	0.101	0.189
IF_s	259,402	0.310	0.242	4.528	51.860	0.094	0.262	0.561
$w_s/w^{\min}$	259,402	3.344	2.149	2.493	12.121	1.568	2.728	5.822

Table A3: Estimated Average Labor an Capital Share by Ownership

We report a linear regression of (log) value-added output $\ln Y_{s,t}$ on (log) quality-adjusted employment $\ln L_{s,t} = \ln(Q_{s,t}N_{s,t})$ and the (log) capital stock $\ln K_{s,t}$ for all firms in Column (1), state-owned enterprises in Column (2), private-owned (Chinese) firms in Column (3), foreign-owned firms in Column (4), and exporting firms in Column (5). Columns (1) and (5) include industry-year-ownership type fixed effects, and Columns (2)-(4) include industry-year fixed effects. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms	SOEs	Private	Foreign	Exporters
	(1)	(2)	(3)	(4)	(5)
$\ln L_{s,t}$	0.531	0.673	0.475	0.596	0.589
	(0.001)***	(0.003)***	(0.001)***	(0.002)***	(0.002)***
$\ln K_{s,t}$	0.309	0.295	0.305	0.297	0.294
	(0.001)***	(0.003)***	(0.001)***	(0.001)***	(0.002)***
Sum of coefficients	0.840	0.968	0.780	0.894	0.883
Ind.FE × Time FE × Ownership FE	Yes	No	No	No	Yes
Ind.FE × Time FE	No	Yes	Yes	Yes	No
Observations	1,201,793	113,287	829,109	259,397	239,252

Table A4: Determinants of Minimum Wage Changes $\Delta \ln w^{\min}$

We explores which local variables influence the minimum wage changes $\Delta \ln w^{\min}$ in China at the county/city level and measure wage growth, changes in the unemployment rate, output growth, and TFP growth at the county/city level. We also break down firm performance in year $t-1$ by firm ownership type (SOEs, private-owned firms, and foreign-owned firms located in the county/city), where the performance measures are (firm size weighted) output growth in Column (2), and stocks returns in Columns (3). In Column (4), we add contemporaneous county/city output growth to the regressors in Column (1).

	(1)	(2)	(3)	(4)
(Log of) average province minimum wage to county/city minimum wage in $t-1$	0.480	0.470	0.469	0.479
	(0.066)***	(0.076)***	(0.078)***	(0.066)***
GDP per capita growth in $t-1$	−0.014	−0.013	−0.011	−0.015
	(0.056)	(0.044)	(0.045)	(0.056)
City wage growth in $t-1$	−0.008	−0.062	−0.057	−0.007
	(0.056)	(0.056)	(0.054)	(0.057)
TFP growth all in $t-1$	0.084	0.020	0.037	0.083
	(0.127)	(0.146)	(0.143)	(0.127)
Output growth all in $t-1$	0.001			
	(0.006)			
TFP growth all in $t-1$	−0.000			
	(0.009)			
Output growth of SOEs in $t-1$		−0.002		
		(0.002)		
Output growth of private firms in $t-1$		−0.000		
		(0.003)		
Output growth of foreign firms in $t-1$		0.003		
		(0.002)*		
TFP growth of SOEs in $t-1$			−0.004	
			(0.003)	
TFP growth of private firms in $t-1$			0.008	
			(0.007)	
TFP growth of foreign firms in $t-1$			0.005	
			(0.003)**	
Stock returns of SOEs in $t-1$				−0.000
				(0.003)
Stock returns of private firms in $t-1$				−0.004
				(0.004)
Stock returns of foreign firms in $t-1$				0.009
				(0.005)
Adjusted R^2	0.053	0.077	0.076	0.052
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
FE for missing values in stock return	No	No	Yes	No
Observations	15,855	10,581	11,349	15,893

Table A5: Robustness Alternative Impact Function Convexity

We replicate the regressions in Table 5 for the total factor productivity growth after minimum wage increases under different impact functions $IF_s = (w^{\min}/w_s)^{1+k}$. The baseline estimates in Table 5 use parameter estimates $\widehat{k} = 0.373$, 0.396 and 0.361 for small, medium and larger firms, respectively. These parameters are obtained via maximum likelihood so as to best account for the observed average firm wage increase under minimum wage shocks. Here we report results for two different specification which simply sets $k = 0$ or $k = 1$. Reported are robust standard errors adjusted for clustering at the county/city-year unit in parentheses and bootstrapped standard errors (accounting for the estimation of $\widehat{k}$ in IF_s) in brackets. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms						Exporters		
	$\widehat{k}$	$k=0$	$k=1$	$\widehat{k}$	$k=0$	$k=1$	$\widehat{k}$	$k=0$	$k=1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IF_s \times \Delta \ln w^{\min}$	0.211	0.164	0.157				0.771	0.699	0.647
	(0.063)***	(0.073)**	(0.044)***				(0.155)***	(0.168)***	(0.133)***
	[0.072]***						[0.180]***		
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$				0.031	0.054	−0.006			
				(0.094)	(0.113)	(0.061)			
				[0.099]					
$IF_s \times \Delta \ln w^{\min} \times D\_private$				0.197	0.135	0.166			
				(0.074)***	(0.088)	(0.053)***			
				[0.079]***					
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$				0.655	0.593	0.470			
				(0.169)***	(0.178)***	(0.156)***			
				[0.183]***					
$\Delta \ln w^{\min}$	−0.039	−0.023	−0.029				−0.108	−0.138	−0.031
	(0.032)	(0.038)	(0.028)				(0.065)*	(0.081)*	(0.053)
IF_s	0.212	0.308	0.093				0.209	0.319	0.084
	(0.008)***	(0.010)***	(0.005)***				(0.018)***	(0.022)***	(0.012)***
All interaction terms with D_x	No	No	No	Yes	Yes	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,110,189	1,110,189	1,110,189	1,110,189	1,110,189	220,287	220,287	220,287

Table A6: Productivity Effect by Ownership Type

The TFP panel regressions from Table 5 are extended to including a triple interaction term $IF_s \times \Delta \ln w^{\min} \times D\_x$ where the dummy D_x marks either state-owned enterprises (D_SOE), or privately owned Chinese companies ($D\_private$), or companies under foreign ownership ($D\_foreign$). The TFP measure $A1$ used in Panel A is calculated on the basis of a firm's cost share for labor and capital averaged over time and $A2$ used in Panel B is calculated on the basis of the industry's cost share averaged over all firms in a given year. Columns (1) and (2) report regression results for the full sample of all firms, while Columns (3)-(4) and (5)-(6) provide the productivity regressions of the subsamples of low- and high-TFP firms, respectively. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county/city-year unit in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level.

Panel A: TFP growth $\Delta \ln A1_{s,t}$

	All firms		Low-TFP firms		High-TFP firms	
	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$	0.064	0.031	0.124	0.078	0.015	-0.008
	(0.094)	(0.094)	(0.123)	(0.122)	(0.142)	(0.143)
$IF_s \times \Delta \ln w^{\min} \times D\_private$	0.222	0.197	0.291	0.268	0.189	0.163
	(0.075)***	(0.074)***	(0.108)***	(0.107)**	(0.085)**	(0.083)*
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$	0.657	0.655	0.963	0.964	0.426	0.429
	(0.173)***	(0.169)***	(0.241)***	(0.229)***	(0.190)**	(0.188)**
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	No	Yes	No	Yes	No	Yes
Observations	1,110,189	1,110,189	520,230	520,228	589,959	589,958

Panel B: TFP growth $\Delta \ln A2_{s,t}$

	All firms		Low-TFP firms		High-TFP firms	
	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$	0.051	0.020	0.116	0.070	0.009	-0.011
	(0.096)	(0.096)	(0.124)	(0.124)	(0.145)	(0.146)
$IF_s \times \Delta \ln w^{\min} \times D\_Private$	0.237	0.213	0.319	0.295	0.193	0.168
	(0.074)***	(0.073)***	(0.105)***	(0.104)***	(0.084)**	(0.083)**
$IF_s \times \Delta \ln w^{\min} \times D\_Foreign$	0.678	0.676	1.009	1.012	0.427	0.428
	(0.168)***	(0.163)***	(0.237)***	(0.225)***	(0.186)**	(0.183)**
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	No	Yes	No	Yes	No	Yes
Observations	1,110,189	1,110,189	520,230	520,228	589,959	589,958

Table A7: Robustness of Productivity Growth to the Inclusion of County-Year Fixed Effects

We repeat the regressions in Table 5 for the total factor productivity growth after minimum wage increases with additional county-year fixed effects. Columns (1), (3), (5), and (7) report the results from Table 5, and Columns (2), (4), (6), and (8) the specifications which include the additional interacted county-year fixed effects. The estimates are robust to these alternative specifications. Reported are robust standard errors adjusted for clustering at the county/city-year unit in parentheses. The last row reports an F-test for equality of the interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms						Exporters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IF \times \Delta \ln w^{\min}$	0.211	0.322					0.771	0.986
	(0.063)***	(0.060)***					(0.155)***	(0.176)***
$IF \times \Delta \ln w^{\min} \times D\_SOE$			0.031	0.132				
			(0.094)	(0.088)				
$IF \times \Delta \ln w^{\min} \times D\_private$			0.197	0.325				
			(0.074)***	(0.063)***				
$IF \times \Delta \ln w^{\min} \times D\_foreign$			0.655	0.581				
			(0.169)***	(0.113)***				
$IF \times \Delta \ln w^{\min} \times D\_low\ TFP$					0.307	0.481		
					(0.083)***	(0.075)***		
$IF \times \Delta \ln w^{\min} \times D\_high\ TFP$					0.173	0.208		
					(0.074)**	(0.066)***		
$\Delta \ln w^{min}$	−0.039						−0.108	
	(0.032)						(0.065)*	
IF	0.212	0.223					0.209	0.223
	(0.008)***	(0.008)***					(0.018)***	(0.021)***
All interaction terms with D_x	No	No	Yes	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,110,189	1,109,478	1,110,189	1,109,478	1,110,189	1,109,478	220,287	216,941
H_0 : Equal interaction (p-value)			0.00	0.00	0.16	0.00		

Table A8: Robustness of Productivity Effect by Management Practice to County-Year Fixed Effects

We repeat the regressions in Table 6 on the role of management practice for firm productivity growth with additional county-year fixed effects. Columns (1), (3), and (5), report the results from Table 5, and Columns (2), (4), and (6) the specifications which include the additional interacted county-year fixed effects. The estimates are robust to these alternative specifications. Reported are robust standard errors adjusted for clustering at the county/city-year unit in parentheses and (block) bootstrapped standard errors in brackets which account for the first-stage estimation of the $Mgmt\_Score$ term. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms		Low-TFP firms		High-TFP firms	
	(1)	(2)	(3)	(4)	(5)	(6)
$IF_s \times \Delta \ln w^{\min} \times Mgmt\_Score$	1.063	0.218	1.638	0.271	0.616	0.185
	(0.402)***	(0.060)***	(0.591)***	(0.089)***	(0.484)	(0.077)**
	[0.403]***		[0.608]***		[0.535]	
$\Delta \ln w^{\min} \times Mgmt\_Score$	0.058	0.229	−0.480	−0.257	0.413	0.557
	(0.170)	(0.126)*	(0.221)**	(0.158)	(0.223)*	(0.167)***
	[0.169]		[0.237]**		[0.228]*	
$IF_s \times Mgmt\_Score$	−0.159	0.310	−0.044	0.342	−0.233	0.292
	(0.052)***	(0.009)***	(0.079)	(0.013)***	(0.058)***	(0.011)***
	[0.099]***		[0.109]		[0.109]***	
$Mgmt\_Score$	−1.746	−1.830	−1.185	−1.258	−2.129	−2.242
	(0.043)***	(0.034)***	(0.057)***	(0.045)***	(0.052)***	(0.042)***
	[0.070]***		[0.076]***		[0.084]***	
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE × Time FE	No	Yes	No	Yes	No	Yes
Observations	1,110,189	1,109,478	520,228	518,874	589,958	588,453

Table A9: Robustness of Exports Effects under County-Year Fixed Effects

We repeat the regressions in Table 7 on the role of effective firm exposure for firm export growth with additional county-year fixed effects. Columns (1), (3), (5), and (7), report the results from Table 7, and Columns (2), (4), (6), and (8) the specifications which include the additional interacted county-year fixed effects. The estimates are robust to these alternative specifications. Reported are robust standard errors for the one-step estimator adjusted for clustering at the county/city-year unit in parentheses. The last row reports an F-test for equality of the interaction coefficients. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	Export value change $\Delta \ln Exp\_Value_{s,t}$				Export volume change $\Delta \ln Exp\_Volume_{s,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IF_s \times \Delta \ln w^{\min}$	0.318	0.453			0.240	0.465		
	(0.180)*	(0.203)**			(0.194)	(0.216)**		
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$			0.906	0.986			0.744	0.935
			(1.066)	(1.296)			(1.031)	(1.206)
$IF_s \times \Delta \ln w^{\min} \times D\_private$			0.090	0.352			−0.173	0.110
			(0.316)	(0.367)			(0.336)	(0.389)
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$			0.533	0.520			0.557	0.664
			(0.214)**	(0.230)**			(0.234)**	(0.245)***
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County.FE × Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	220,287	216,941	220,287	216,941	212,717	209,357	212,717	209,357
H_0 : Equal interaction (p-value)			0.45	0.85			0.18	0.42

Table A10: Production Parameter Inference under Different Estimation Methods

We estimate the parameters α_L and α_K of a Cobb-Douglas production function in value added output $\ln Y = \ln A + \alpha_L \ln(L) + \alpha_K \ln(K)$ using the cost share method, the LP method and the ACF method. Estimates are reported for all firms, by firm ownership type and by industry. Column (1) provides the number of firm-years used in each estimation which covers the period 2001-2008. Columns (2), (5), and (8) report the labor coefficient (for quality adjusted labor); Columns (3), (6), and (9) the capital coefficient; and Columns (4), (7), and (10) the sum of the labor and capital coefficient, respectively.

	Obs	Cost Share Method			LP Method			ACF Method		
		α_L (1)	α_K (2)	$\alpha_L+\alpha_K$ (3)	α_L (4)	α_K (5)	$\alpha_L+\alpha_K$ (6)	α_L (7)	α_K (8)	$\alpha_L+\alpha_K$ (9)
All firms	1,299,864	0.578	0.422	1	0.183	0.260	0.371	0.315	0.442	0.686
Firms by ownership type										
SOEs	138,010	0.522	0.478	1	0.254	0.191	0.267	0.168	0.445	0.436
Private	882,891	0.585	0.415	1	0.175	0.250	0.380	0.282	0.425	0.662
Foreign-owned	278,963	0.586	0.414	1	0.256	0.297	0.009	0.657	0.553	0.665
Firms by industry										
Coal mining	23,485	0.658	0.342	1	0.269	0.234	0.732	0.053	0.503	0.785
Crude petroleum and natural gas	257	0.208	0.792	1	0.186	0.591	0.319	0.538	0.776	0.857
Iron ores	3,263	0.548	0.452	1	0.238	0.250	0.776	0.003	0.488	0.779
Miscellaneous metal ores	5,889	0.535	0.465	1	0.211	0.211	0.403	−0.056	0.421	0.347
Nonmetallic minerals	7,112	0.575	0.425	1	0.142	0.134	0.032	0.451	0.276	0.483
Mining services	69	0.533	0.467	1	−0.102	0.377	7.291	1.122	0.275	8.413
Food processing	63,475	0.495	0.505	1	0.045	0.277	0.225	0.260	0.322	0.484
Prepared food	26,791	0.524	0.476	1	0.130	0.220	0.400	0.160	0.350	0.559
Beverages	18,341	0.468	0.532	1	0.172	0.244	0.438	0.037	0.416	0.474
Tobacco products	783	0.451	0.549	1	0.334	0.338	−0.613	0.399	0.672	−0.214
Textile products	109,269	0.587	0.413	1	0.212	0.221	0.526	0.135	0.434	0.660
Apparel	55,549	0.754	0.246	1	0.321	0.185	0.135	0.391	0.506	0.526
Leather products and footwear	38,305	0.732	0.268	1	0.248	0.211	0.558	0.154	0.459	0.712
Lumber processing	26,955	0.612	0.388	1	0.172	0.257	0.427	0.202	0.429	0.629
Furniture	14,425	0.647	0.353	1	0.168	0.270	0.357	0.243	0.438	0.600
Papers and allied products	37,121	0.529	0.471	1	0.195	0.305	0.532	0.175	0.500	0.707
Printing and recording media	25,039	0.511	0.489	1	0.226	0.224	0.537	0.070	0.451	0.607
Recreational products	38,777	0.709	0.291	1	0.279	0.192	0.590	0.099	0.470	0.689
Petroleum processing	10,346	0.445	0.555	1	0.109	0.218	0.115	0.558	0.327	0.673
Chemical products	87,965	0.519	0.481	1	0.158	0.318	0.309	0.325	0.476	0.634
Medical and pharmaceutical products	26,161	0.483	0.517	1	0.131	0.184	0.413	0.157	0.315	0.570
Synthetic fiber	6,444	0.427	0.573	1	0.098	0.305	0.666	0.208	0.403	0.875
Rubber and plastic products	70,512	0.559	0.441	1	0.150	0.268	0.481	0.206	0.418	0.687
Nonmetal mineral products	106,248	0.522	0.478	1	0.155	0.240	0.538	0.123	0.395	0.661
Smelting of ferrous metals	43,494	0.562	0.438	1	0.149	0.269	0.066	0.555	0.418	0.621
Smelting of nonferrous metals	17,213	0.526	0.474	1	0.067	0.309	0.190	0.345	0.376	0.535
Metal products	74,843	0.612	0.388	1	0.162	0.229	0.185	0.411	0.391	0.595
Standard machinery	81,356	0.612	0.388	1	0.156	0.224	0.462	0.222	0.380	0.685
Special machinery	58,912	0.617	0.383	1	0.155	0.275	0.403	0.320	0.430	0.722
Motor vehicles	32,711	0.581	0.419	1	0.135	0.267	0.329	0.336	0.402	0.666
Railroad equipment and aircraft	17,930	0.640	0.360	1	0.174	0.220	0.144	0.480	0.394	0.624
Electrical machinery and equipment	69,827	0.611	0.389	1	0.170	0.256	0.221	0.498	0.426	0.719
Computer communications equipment	40,128	0.622	0.378	1	0.278	0.285	0.300	0.455	0.563	0.756
Apparatus	15,684	0.675	0.325	1	0.263	0.244	0.328	0.480	0.507	0.808
Miscellaneous manufacturing	4,942	0.703	0.297	1	0.246	0.134	1.081	−0.069	0.380	1.012
Waste management	1,052	0.577	0.423	1	0.252	0.306	0.480	0.320	0.558	0.800
Electric services	26,221	0.335	0.665	1	0.149	0.238	−0.391	0.886	0.387	0.495
Gas services	2,418	0.376	0.624	1	0.050	0.225	0.647	0.207	0.275	0.855
Water supply	10,552	0.437	0.563	1	0.614	0.180	0.399	0.287	0.794	0.686

Table A11: Robustness of Productivity Effect under the LP and ACF Method

We repeat the regressions in Table 5 for alternative measures of total factor productivity. In Panel A we use as the dependent variable TFP growth based on an industry specific production function estimated by the LP method, and in Panel B the parameters of the production functions are based on estimates obtained from the ACF method. The last two rows reports an F-test for equality of the interaction coefficients.

	All firms				SOEs	Foreign	Exporters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Total factor productivity growth based on the LP method							
$IF_s \times \Delta \ln w^{\min}$	0.177	0.168			−0.019	0.494	0.549
	(0.056)***	(0.055)***			(0.097)	(0.148)***	(0.138)***
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$			−0.009				
			(0.090)				
$IF_s \times \Delta \ln w^{\min} \times D\_private$			0.172				
			(0.066)***				
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$			0.510				
			(0.149)***				
$IF_s \times \Delta \ln w^{\min} \times D\_low\ TFP$				0.253			
				(0.075)***			
$IF_s \times \Delta \ln w^{\min} \times D\_high\ TFP$				0.137			
				(0.066)**			
$\Delta \ln w^{\min}$	−0.056	−0.035			0.075	−0.018	−0.045
	(0.030)*	(0.029)			(0.039)*	(0.066)	(0.061)
IF_s	0.149	0.151			0.124	0.166	0.146
	(0.007)***	(0.007)***			(0.016)***	(0.017)***	(0.016)***
Panel B: Total factor productivity growth based on the ACF method							
$IF_s \times \Delta \ln w^{\min}$	0.207	0.197			−0.003	0.564	0.637
	(0.058)***	(0.057)***			(0.099)	(0.152)***	(0.143)***
$IF_s \times \Delta \ln w^{\min} \times D\_SOE$			0.008				
			(0.092)				
$IF_s \times \Delta \ln w^{\min} \times D\_private$			0.197				
			(0.068)***				
$IF_s \times \Delta \ln w^{\min} \times D\_foreign$			0.574				
			(0.153)***				
$IF_s \times \Delta \ln w^{\min} \times D\_low\ TFP$				0.293			
				(0.077)***			
$IF_s \times \Delta \ln w^{\min} \times D\_high\ TFP$				0.157			
				(0.068)**			
$\Delta \ln w^{min}$	−0.064	−0.040			0.078	−0.036	−0.070
	(0.030)**	(0.030)			(0.040)**	(0.067)	(0.062)
IF_s	0.179	0.181			0.149	0.193	0.175
	(0.007)***	(0.007)***			(0.016)***	(0.018)***	(0.017)***
All interaction terms with D_x	No	No	Yes	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE × Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,110,189	1,110,189	1,110,189	101,600	242,518	220,287
H_0 : Eq. interaction (A) (p-value)			0.01	0.19			
H_0 : Eq. interaction (B) (p-value)			0.01	0.13			

Table A12: Management Scores Predicting Firm Ownership Type

We test the predictive power of management scores ($Mgmt\_Score$) of the survey sample in Bloom and Reenen (2010) for the ownership type of Chinese firms. Columns (1)-(3) report OLS regressions in which the binomial variable *Private_vs_SOE* (1 = Private owned, 0 = SOE) is regressed on the management scores while controlling for firm TFP (relative to the industry average), log employees, industry fixed effects and year fixed effects. Columns (4)-(6) report similar OLS regressions for the binomial variable *Foreign_vs_SOE* (1 = Foreign owned, 0 = SOE). We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	Private_vs_SOE (1 = Private owned, 0 = SOE)			*Foreign_vs_SOE* (1 = Foreign owned, 0 = SOE)		
	(1)	(2)	(3)	(4)	(5)	(6)
$Mgmt\_Score$	0.036		0.065	0.125		0.142
	(0.066)		(0.078)	(0.045)***		(0.060)**
TFP (relative to industry)		0.094	0.094		0.077	0.074
		(0.033)***	(0.033)***		(0.028)***	(0.028)***
$\ln(N)$	−0.083	−0.109	−0.118	−0.052	−0.058	−0.078
	(0.028)***	(0.035)***	(0.036)***	(0.022)**	(0.030)*	(0.031)**
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.32	0.32	0.29	0.26	0.28
R^2 adjusted	0.13	0.20	0.20	0.22	0.18	0.19
Observations	269	190	190	343	244	244

Table A13: Firm Ownership Type Predicting Management Scores

We test the predictive power of the ownership dummies ($D\_private$) and ($D\_foreign$) for the management scores ($Mgmt\_Score$) of Chinese firms. All regressions control for firm size measured by log employment [$\ln(N)$], industry fixed effects and time fixed effects. Columns (2)-(3) control also for a firm TFP (relative to the industry average). We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	$Mgmt\_Score$		
	(1)	(2)	(3)
$D\_private$	0.047		0.034
	(0.065)		(0.078)
$D\_foreign$	0.197		0.203
	(0.064)***		(0.073)***
TFP (relative to industry)		−0.017	−0.014
		(0.025)	(0.026)
$\ln(N)$	0.103	0.132	0.127
	(0.020)***	(0.027)***	(0.027)***
Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.24	0.19	0.22
R^2 adjusted	0.19	0.12	0.15
F-*statistics*	14.75	12.39	10.13
Observations	548	386	386

Table A14: Labor Shares and TFP growth compared with Hsieh and Klenow (2009)

We report medians of firm labor shares and firm TFP growth rates for each 2-digit manufacturing industry. Columns (1) and (4) labeled HHW present our results, and Columns (2) and (5) labeled HK present results based on Hsieh and Klenow (2009). In Columns (3) and (6) we report the correlation for labor shares and TFP growth, respectively, across all firms in each 2-digit industry. Our labor shares (HHW) are the ratios of a firm's wage bill to total production cost (the sum of wage bills and capital cost). The approach in Hsieh and Klenow (HK) first scales up a firm's labor compensations by a factor such that a 50% aggregate labor share is obtained for all Chinese manufacturing firms. The labor shares are then calculated as the ratio of firm labor compensations to value added. Generally, the both methods produce firm TFP growth values with a very high correlation.

	Labor shares			TFP growth		
Industry	HHW	HK	Corr.	HHW	HK	Corr.
	(1)	(2)	(3)	(4)	(5)	(6)
13 food processing	0.49	0.27	0.12	0.11	0.10	0.98
14 prepared food	0.52	0.46	0.16	0.19	0.19	0.99
15 beverages	0.46	0.37	0.11	0.21	0.20	0.99
16 tobacco products	0.42	0.40	0.04	0.16	0.14	0.97
17 textile products	0.59	0.64	0.20	0.15	0.15	0.99
18 apparel	0.78	0.87	−0.02	0.13	0.14	0.99
19 leather products and footwear	0.77	0.99	0.40	0.10	0.11	0.98
20 lumber processing	0.63	0.49	0.19	0.17	0.16	0.98
21 furniture	0.66	0.72	0.07	0.15	0.16	0.99
22 papers and allied products	0.52	0.52	0.14	0.13	0.13	0.99
23 printing and recording media	0.50	0.61	0.08	0.12	0.12	0.98
24 recreational products	0.74	0.87	0.17	0.10	0.12	0.98
25 petroleum processing	0.42	0.29	0.08	0.02	0.01	0.98
26 chemical products	0.52	0.40	0.17	0.11	0.10	0.98
27 medical and pharmaceutical products	0.47	0.45	0.07	0.17	0.17	0.99
28 synthetic fiber	0.42	0.36	0.06	0.15	0.15	0.99
29 rubber and plastic products	0.56	0.58	0.21	0.11	0.12	0.98
30 nonmetal mineral products	0.51	0.49	0.20	0.17	0.18	0.98
31 smelting of ferrous metals	0.57	0.43	0.23	0.18	0.17	0.98
32 smelting of nonferrous metals	0.53	0.35	−0.01	−0.08	−0.09	0.98
33 metal products	0.62	0.53	0.16	0.16	0.16	0.98
34 standard machinery	0.62	0.62	−0.00	0.17	0.17	0.99
35 special machinery	0.62	0.64	−0.00	0.15	0.15	0.98
36 motor vehicles	0.59	0.59	0.05	0.17	0.17	0.99
37 railroad equipment and aircraft	0.65	0.70	0.11	0.17	0.18	0.98
38 electrical machinery and equipment	0.62	0.52	0.28	0.11	0.10	0.98
39 computer communications equipment	0.64	0.61	0.07	0.16	0.16	0.99
40 apparatus	0.69	0.74	0.06	0.11	0.12	0.98
41 miscellaneous manufacturing	0.71	0.83	−0.08	0.10	0.10	0.99

Table A15: Labor Shares and TFP growth comparison with Brandt et al. (2017)

We report medians of firm labor shares and firm TFP growth rates for each 2-digit manufacturing industry. Columns (1) and (4) report our results labeled HHW. Columns (2)-(3) and (5)-(6) present results following the approach taken in Brandt *et al.* (2017) labeled BBWZ. Columns (7) and (8) report the correlations between TFP growth following the HHW and BBWZ method among firms in each 2-digit industry. Our labor shares are the ratios of firm wage bills to total production cost (the sum of wage bills and capital cost). For the approach in Brandt *et al.* (2017), we calculate the labor shares as $\beta_l/(\beta_l+\beta_k)$ and label it BBWS(1); or compute the labor share alternatively as $\beta_l/(1-\beta_m)$ and label it BBWS(2), where $\beta_l, \beta_k, \beta_m$ are the estimated factor elasticities for labor, capital, and intermediate input, respectively, as reported in Table A.2 of Brandt *et al.* (2017). Generally, the alternative methods produce firm TFP growth values which a very high correlation.

Industry	Labor shares			TFP growth				
	HHW	BBWZ(1)	BBWZ(2)	HHW	BBWZ(1)	BBWZ(2)	Corr.(1)	Corr.(2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
13 food processing	0.49	0.56	0.40	0.11	0.11	0.11	0.99	0.99
14 prepared food	0.52	0.73	0.71	0.19	0.21	0.20	0.98	0.98
15 beverages	0.46	0.57	0.58	0.21	0.21	0.21	0.99	0.99
16 tobacco products	0.43	0.17	0.29	0.16	0.15	0.15	0.97	0.98
17 textile products	0.60	0.63	0.27	0.15	0.15	0.13	0.99	0.96
18 apparel	0.79	0.80	0.81	0.13	0.13	0.13	0.99	0.99
19 leather products and footwear	0.77	0.72	0.71	0.10	0.10	0.10	0.99	0.99
20 lumber processing	0.64	0.77	0.61	0.17	0.18	0.17	0.98	0.99
21 furniture	0.66	0.74	0.65	0.15	0.16	0.15	0.99	0.99
22 papers and allied products	0.52	0.81	0.74	0.13	0.15	0.14	0.97	0.98
23 printing and recording media	0.50	0.53	0.56	0.12	0.11	0.12	0.99	0.99
24 recreational products	0.74	0.75	0.74	0.10	0.11	0.10	0.99	0.99
25 petroleum processing	0.43	0.53	0.41	0.02	0.02	0.02	0.99	0.99
26 chemical products	0.52	0.30	0.18	0.11	0.09	0.09	0.98	0.96
27 medical and pharmaceutical products	0.47	0.50	0.45	0.17	0.17	0.17	0.99	0.99
28 synthetic fiber	0.41	0.07	0.05	0.15	0.14	0.14	0.96	0.96
29 rubber and plastic products	0.56	0.58	0.46	0.11	0.12	0.11	0.99	0.99
30 nonmetal mineral products	0.51	0.64	0.57	0.17	0.18	0.18	0.98	0.99
31 smelting of ferrous metals	0.57	0.76	0.84	0.18	0.19	0.20	0.98	0.97
32 smelting of nonferrous metals	0.53	1.00	1.18	−0.08	−0.04	−0.02	0.95	0.91
33 metal products	0.63	1.00	1.01	0.16	0.19	0.19	0.93	0.93
34 standard machinery	0.62	0.55	0.43	0.17	0.16	0.16	0.99	0.98
35 special machinery	0.63	0.32	0.21	0.15	0.13	0.13	0.97	0.95
36 motor vehicles	0.59	0.41	0.25	0.17	0.16	0.15	0.98	0.96
37 railroad equipment and aircraft	0.65	0.44	0.35	0.17	0.15	0.15	0.98	0.96
38 electrical machinery and equipment	0.62	0.61	0.50	0.11	0.10	0.10	0.99	0.99
39 computer communications equipment	0.64	0.55	0.50	0.16	0.15	0.15	0.99	0.99
40 apparatus	0.69	0.67	0.61	0.11	0.11	0.10	0.99	0.99
41 miscellaneous manufacturing	0.72	0.98	1.19	0.10	0.12	0.15	0.96	0.91

Table A16: Regression Results for TFP Growth Calculated by Different Sets of Labor Shares

We report regression results on TFP growth based (i) on our method (HHW) in Column (1), (ii) following Hsieh and Klenow (2009) in Column (2), and (iii) following Brandt et al. (2017) in Columns (4) and (5). Column (1) and (2) use the labor shares reported in Table A14. Column (3) labeled HHW(ACF) uses the labor shares estimated by the ACF method for our firm sample at the level of each 2-digit industry. This differs from Table A11, which uses uniform labor shares for all the industries. Column (4) and (5) use TFP growth for the labor shares shown in Table A15. In Panel A, we report the simple specification with the impact factor interacted with minimum wage growth. Panel B shows the extended specification with triple interaction terms. Reported are robust standard errors for the one-step estimated adjusted for clustering at the county/city-year unit in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively. The estimation results are robust to these alternative methods of inferring TFP growth.

Panel A: Simple Specification for Productivity Growth $\Delta \ln A$

	Non-parametric		ACF estimation		
	HHW	HK	HHW(ACF)	BBWZ(1)	BBWZ(2)
	(1)	(2)	(3)	(4)	(5)
$IF \times \Delta \ln w^{\min}$	0.211	0.178	0.213	0.232	0.205
	(0.063)***	(0.064)***	(0.063)***	(0.064)***	(0.064)***
$\Delta \ln w^{\min}$	−0.039	−0.042	−0.051	−0.053	−0.049
	(0.032)	(0.035)	(0.035)	(0.035)	(0.035)
IF	0.212	0.205	0.202	0.212	0.197
	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Ind. × Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,042,839	1,042,839	1,042,839	1,042,839

Panel B: Extended Specification for Productivity Growth $\Delta \ln A$

	Non-parametric		ACF estimation		
	HHW	HK	HHW(ACF)	BBWZ (1)	BBWZ (2)
	(1)	(2)	(3)	(4)	(5)
$IF \times \Delta \ln w^{\min} \times SOE$	0.031	0.067	0.073	0.073	0.074
	(0.094)	(0.107)	(0.106)	(0.105)	(0.105)
$IF \times \Delta \ln w^{\min} \times PRV$	0.197	0.137	0.186	0.205	0.180
	(0.074)***	(0.074)*	(0.074)**	(0.074)***	(0.075)**
$IF \times \Delta \ln w^{\min} \times FORN$	0.655	0.597	0.551	0.594	0.533
	(0.169)***	(0.165)***	(0.159)***	(0.164)***	(0.163)***
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Ind. × Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,110,189	1,042,839	1,042,839	1,042,839	1,042,839