

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

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Abstract

The large regional variation in minimum wage levels in 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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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. The largest benefits from competitive shocks may even 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. In a series of papers, Bloom, *et al.* (2010) and Bloom and van Reenen (2007, 2010) have documented the positive correlation between firm productivity 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

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

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 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 for 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 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

²The 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.

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; Akerberg *et al.* 2007). 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 tries to provide a coherent interpretation of 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 A3 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 studied in the previous literature. Trade agreements represent a different regulatory shock which can exogenously intensify competition 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 accelerate productivity growth. Lileeva and Trefler (2010) look at the response

³Political 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.

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

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.

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.

Our most important result concerns the endogenous productivity response to higher minimum wages by Chinese 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

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

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 Haepf and Lin (2015) also 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

⁶We 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.

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 (The Economist, 2016; 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).

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 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,

⁷Plausible 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 Efung *et al.* (2016).

we can define an *impact function* (IF) as follows

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

In the empirical part, we estimate the impact function using the functional form $IF(w_s/w^{\min}) = \lambda (w_s/w^{\min})^{-(k+1)}$, 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 $IF_s \Delta \ln w^{\min}$.

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

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

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 SOE employees in the period 1998-2007, when approximately 80% of SOEs either terminated their activity or were re-structured 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. Recent 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 heterogenous and dependent on management quality. The observed patterns of endogenous productivity response to minimum wage shocks support the “managerial” view of the firm.

⁹Only 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)

¹⁰This 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 In particular, the timing of the minimum wage change may largely be determined by internal party politics, which can be considered 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% 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

¹¹The 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.

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 data 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 1,192,144 firm-year observations. A breakdown of the sample by ownership type yields 104,709 firm-years observations for state-owned enterprises (SOEs), 825,907 observations for private-owned firms (in Chinese ownership) and 261,528 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.

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 19.4%, followed by foreign owned firms at 15.1% and SOEs with only 8.8%. Similarly, annual productivity growth is largest for privately owned firms (at 13.3% and 13.5%, for $\Delta \ln(A1)$ and $\Delta \ln(A2)$, respectively), followed by foreign owned firms (at 10.3% and 10.4%) and SOEs (at 9.4% and 9.5%). Correspondingly, the capital intensity, as measured by the (log) capital to labor ratio $\ln(K/N)$, grows faster for private-owned firms at 10.7% compared with only 5.6% and 5.3% for foreign owned firm and SOEs, respectively.¹²

One shortcoming of the Annual Survey of Industrial Firms (ASIF) is a lack of firm-specific

¹²Detailed summary statistics by firm ownership and initial TFP level are reported in Table A2 in the Web Appendix to this paper.

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 24.1% in value terms for the period 2000-08. For exporting firms, we show in Section 7.2 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.

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 Δw^{\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

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

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

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

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 Δw^{\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 0.373 for small firms compared to 0.396 and 0.361 for medium and large firms, respectively. A parameter of 0.37 implies that a low-wage firm facing a minimum wage of 80% of its average wage will be exposed 67% more (in absolute terms) to any minimum wage increase $[(0.8)^{0.37}/(0.2)^{0.37} = 1.67]$ 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 6.68 times larger $[(0.8)^{1.37}/(0.2)^{1.37} = 6.68]$ 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 $k + 1 = 1.373, 1.396, \text{ and } 1.361$, 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 $[IF_s \times \Delta \ln w^{\min}]$ increases further. In Column (3), a coefficient estimate $\hat{\beta} = 1.923$ implies 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 ($w_s/w^{\min} = 1.409$) of the wage distribution increases its (log) average wage $\ln w_s$ by 20.7% [$= 1.923 \times (1.409)^{-1.373} \times 0.2 - 0.166 \times 0.2$] compared to only 1.3% [$= 1.923 \times (4.683)^{-1.373} \times 0.2 - 0.166 \times 0.2$] for a high-wage firm at the 90% wage quantile ($w_s/w^{\min} = 4.683$). 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 $IF_s = (w_s/w^{\min})^{-(k+1)}$, 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

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

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.

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

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 0.346 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 0.119, respectively. The firm difference in the labor to capital substitution follows as 3.53% [= $0.346 \times (0.629 - 0.119) \times 0.2$], compared to an annual average substitution rate of 9.1%. 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 0.346 for the average labor to capital substitution under the treatment effect $IF_s \times \Delta w^{\min}$ to the corresponding coefficient of 1.923 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

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

The observed average adjustment in the capital to labor ratio is only 1/5 of the predicted change. For the foreign firms, the corresponding point estimate of 0.644 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 4 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 0.333 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 SOE, 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 marking 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,

$$\begin{aligned} \Delta \ln Z_{s,t} = & \sum_x \beta_x [IF_s \times \Delta \ln w^{\min} \times D_x] + \sum_x \delta_x [\Delta \ln w^{\min} \times D_x] + \\ & + \sum_x \gamma_x [IF_s \times D_x] + \sum_x \theta_x D_x + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}, \end{aligned} \quad (6)$$

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 $\hat{\beta}_{foreign} = 0.498$ for (value added) output growth, compared to $\hat{\beta}_{private} = 0.172$ 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 similar for firms initially below or above the median industry TFP.

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 $w_s/w^{\min} = 1.557$) by -4.0% [= $-0.367 \times (1.557)^{-1.361} \times 0.2$] compared to -0.7% [= $-0.367 \times (5.716)^{-1.361} \times 0.2$] for high-wage firms (at the 90% quantile where $w_s/w^{\min} = 5.716$) in the same industry sector. From Column (6) we infer that the relative employment growth reduction is twice as larger 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. The increased capital spending is concentrated in firms which already have an initial TFP level above the median.

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

$$\frac{\Delta \ln A}{IF_s \times \Delta \ln w^{\min}} = \Delta \ln Y - \frac{2}{3} \Delta \ln N - \frac{1}{3} \Delta \ln K = 0.22 + \frac{2}{3} \times 0.275 - \frac{1}{3} \times 0.084 = 0.375.$$

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 $Y_{s,t} = \text{Gross Revenue}_{s,t}/p_Y - \text{Cost Intermediate Goods}_{s,t}/p_X$, 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

$$\begin{aligned}\Delta \ln A_{s,t} &= \ln A_{s,t} - \ln A_{s,t-1} = \\ &= \ln Y_{s,t} - \ln Y_{s,t-1} - \alpha_L(\ln w_{s,t-1}N_{s,t} - \ln w_{s,t-1}N_{s,t-1}) - \alpha_K(\ln K_{s,t} - \ln K_{s,t-1}).\end{aligned}\tag{7}$$

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.¹⁴ We find that output regressions on factor inputs or more advanced estimation techniques (Olley and Pakes, 1996) 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

$$\alpha_L = \alpha_L(s, t) = \frac{w_{s,t-1}N_{s,t}}{w_{s,t-1}N_t + rK_{s,t}} \quad \text{and} \quad \alpha_K = \alpha_K(s, t) = \frac{rK_{s,t}}{w_{s,t-1}N_{s,t} + rK_{s,t}},\tag{8}$$

respectively. For the cost of capital, we assume a constant rate $r = 7\%$ for all firms.¹⁵

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, 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

¹⁴The Chinese firm data are based on firm surveys and collected independently of the internal accounting procedures of the firms. We also note that career concerns may provoke deliberate misreporting if the survey data are suspected of being used for ulterior performance evaluations and comparisons.

¹⁵Using 5% or 9% instead did not qualitatively change any of the results.

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

$$\Delta \ln A_{1s,t} = \beta [IF_s \times \Delta \ln w^{\min}] + \gamma IF_s + \delta \Delta \ln w^{\min} + \mu_{Ind \times Year} + \nu_s + \epsilon_{s,t}, \quad (9)$$

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 extent 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 $\hat{\beta} = 0.261$ 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

$$\frac{\Delta \ln A}{IF_s \times \Delta \ln w^{\min}} = \Delta \ln Y - \frac{2}{3} \Delta \ln N - \frac{1}{3} \Delta \ln K = 0.171 + \frac{2}{3} \times 0.193 - \frac{1}{3} \times 0.153 = 0.249.$$

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 $\hat{\beta} = 0.234$ 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 $\hat{\beta}_{foreign} = 0.723$. The point estimate of $\hat{\beta}_{foreign} = 0.723$ 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 $w_s/w^{\min} = 1.557$) by 7.9% [= $0.723 \times (1.557)^{-1.361} \times 0.2$] compared to 1.3% [= $0.723 \times (5.716)^{-1.361} \times 0.2$] for a high-wage firms (at the 90% quantile where $w_s/w^{\min} = 5.716$) in the same industry sector. By comparison,

the average annual TFP growth among foreign-owned firms is 10.3%. The additional TFP growth of 7.9% 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 regression for SOEs and foreign-owned firms. The point estimates for the subsamples are very similar to the corresponding coefficients in Column (4) at $\hat{\beta}_{SOE} = 0.026$ for SOEs [Column (6)] and $\hat{\beta}_{foreign} = 0.690$ 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 $D_{low-TFP}$ has a coefficient twice as large as the corresponding term interacted with the dummy $D_{high-TFP}$. The coefficient $\hat{\beta}_{low-TFP} = 0.409$ is again close to the productivity growth effect of 0.375 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 sort firms by their initial TFP into a high- and low-TFP subsample and repeat the regression in Table 5, Column (4). These additional regressions (reported in Table A5 of the Internet Appendix) show again that firms with a low initial TFP experience a much larger TFP acceleration. However, 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 A5 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.¹⁶

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 7.3 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 exports quantity which is consistent with our finding of a productivity surge. Particularly for foreign-owned firms we can 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. Yet SOEs show no evidence for a corresponding 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 expenditure under an adverse labor cost shock, but no such reaction is seen for SOEs. We note that capital constraints 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

¹⁶The 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.

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).¹⁷ 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 can transform them into conditional measures which adjust for firm size (log assets), 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.

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 asset).

¹⁷Compare Bloom *et al.* (2010) and Bloom and van Reenen (2007, 2010).

Assuming the representativeness of the survey sample, we then predict the management scores (*Mgmt_Score*) of all other firms based on ownership type and firm size.¹⁸ 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 A11 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 1.368 for the triple interaction term in Column (6) 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 5.5% in the year of the minimum wage increase.¹⁹ 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.

The sample difference for *Mgmt_Score* between foreign-owned firms and SOEs is 0.173. Multiplied by the point estimate of 1.368 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 2.4%, which is less than the incremental productivity growth difference of 13.2% shown

¹⁸This 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 39.9. The results of the first stage regression are reported in Table A10, Column (1), of the Internet Appendix.

¹⁹The 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 $IF_s \times \Delta \ln w^{\min} = 0.102$.

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 (6), 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 the true management quality of Chinese firms. 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

This section explores the stability of the results in three dimensions. First, we verify that alternative inferences about the productivity parameters α_L and α_K of the production function confirm the results described in the previous section. A second robustness check 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. Third, we use an independent data source from the

Chinese customs authorities to show that the relative productivity surge in private-owned and foreign-owned firms after minimum wage hikes is also reflected in higher export volumes. This finding makes output and output price mismeasurement an implausible explanation for the evidence.

7.1 Alternative Productivity Measures

In Section 6.3, 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 0.723 to 0.742 with almost the same standard errors.²⁰ 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 $\hat{\alpha}_{L/K}(s, t)$ 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. Akerberg, Caves, and Frazer (2015) propose a further generalization. We implement

²⁰We report these results in Table A5 of the Web Appendix.

both methods as a robustness check in the Internet Appendix, where Table A8 compares the coefficient estimates for each industry across three methods. Panel A and B of Table A9 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 structure. In spite of this sensitivity of the production parameters, 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 0.955 and 0.973 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.²¹

7.2 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

²¹In 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).

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

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 -0.193 and 0.153 , respectively. For $\alpha = 2/3$, the resulting TFP measurement bias is quantified as

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

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% ($= 0.0156/0.723$) 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.

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 revenues, intermediary product inputs, 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.

7.3 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 0.0004 (or 0.0007). 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.²²

7.4 Output Mismeasurement

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 89,068 firm-year observations. Approximately, 65% 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

²²In a related paper, Mayneris, Poncet, and Zhang (2015) 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.

(though not statistically significant), 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 price effect is -0.009 with a very small (bootstrapped) standard error of only 0.104. 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 0.806 in Table 5, Column (8), as the latter is approximately eight standard deviations higher than the (near zero) point estimate of -0.009 for the output price effect.²³

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-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

²³As 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)

and van Reenen (2011) find no evidence of wage pass-through among listed firms.

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 is 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 organiza-

tions and firms responsive to competitive challenges and causes productivity growth.

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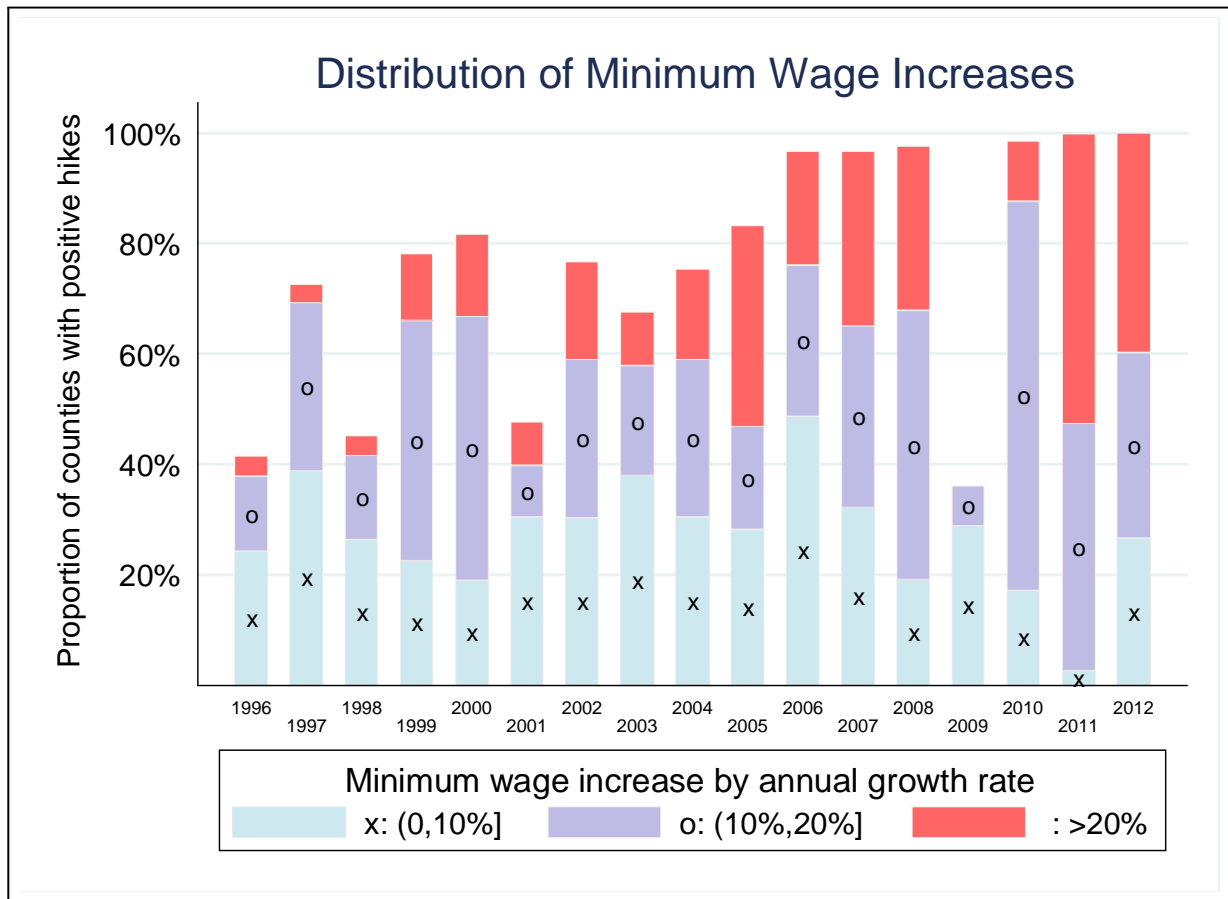


Figure 1: We plot by year the percentage of China's 2,867 counties with a strictly positive minimum wage change between 0 and 10%, between 10% and 20%, and above 20%, respectively.

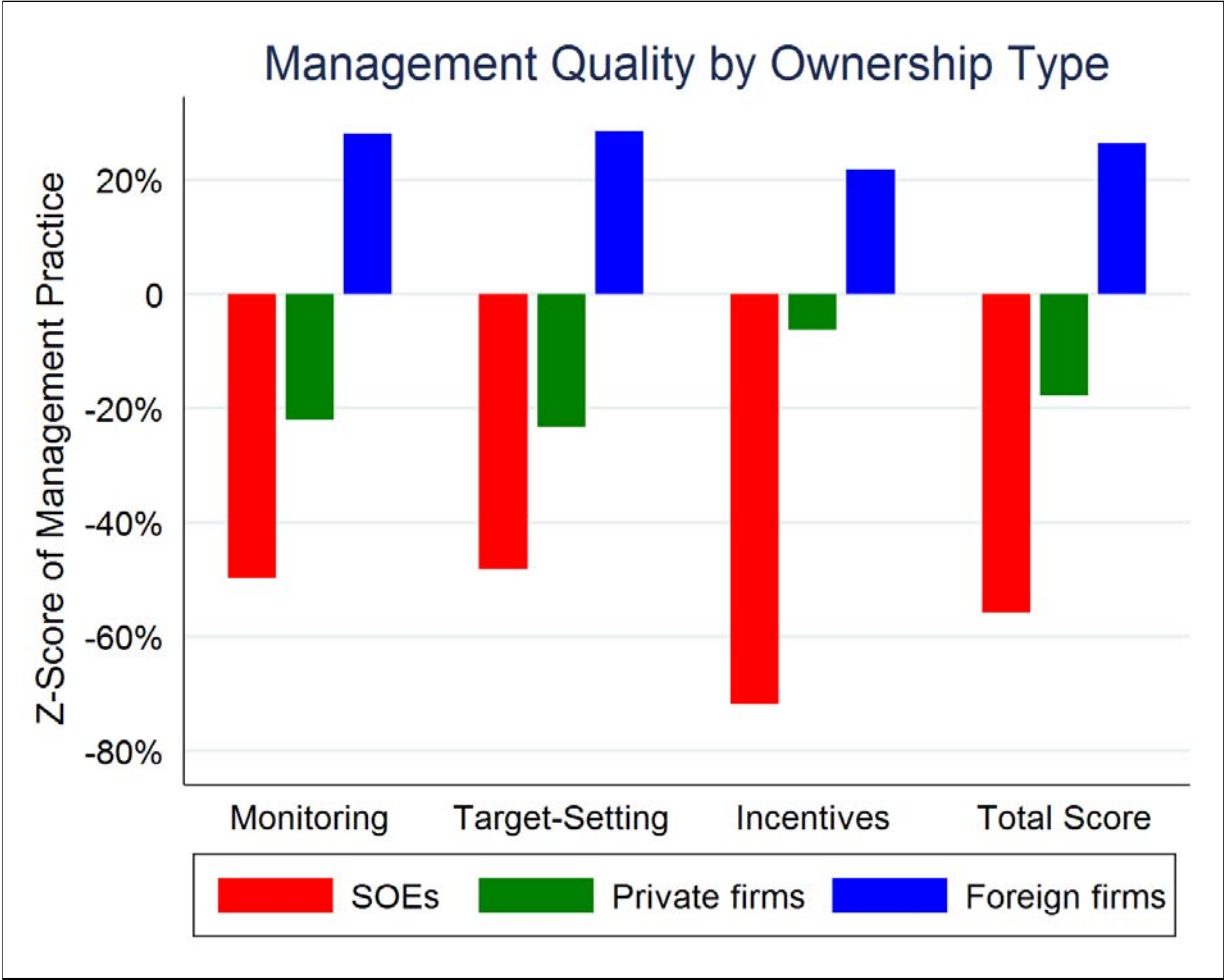


Figure 2: Based on survey data collected by Bloom and van Reenen (2010) on management practices in 564 Chinese firms sampled in 2006, 2007 and 2008, we report a breakdown of these scores by firm ownership (SOEs, private-owned firms, foreign-owned firms) after controlling for firm size and industry and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

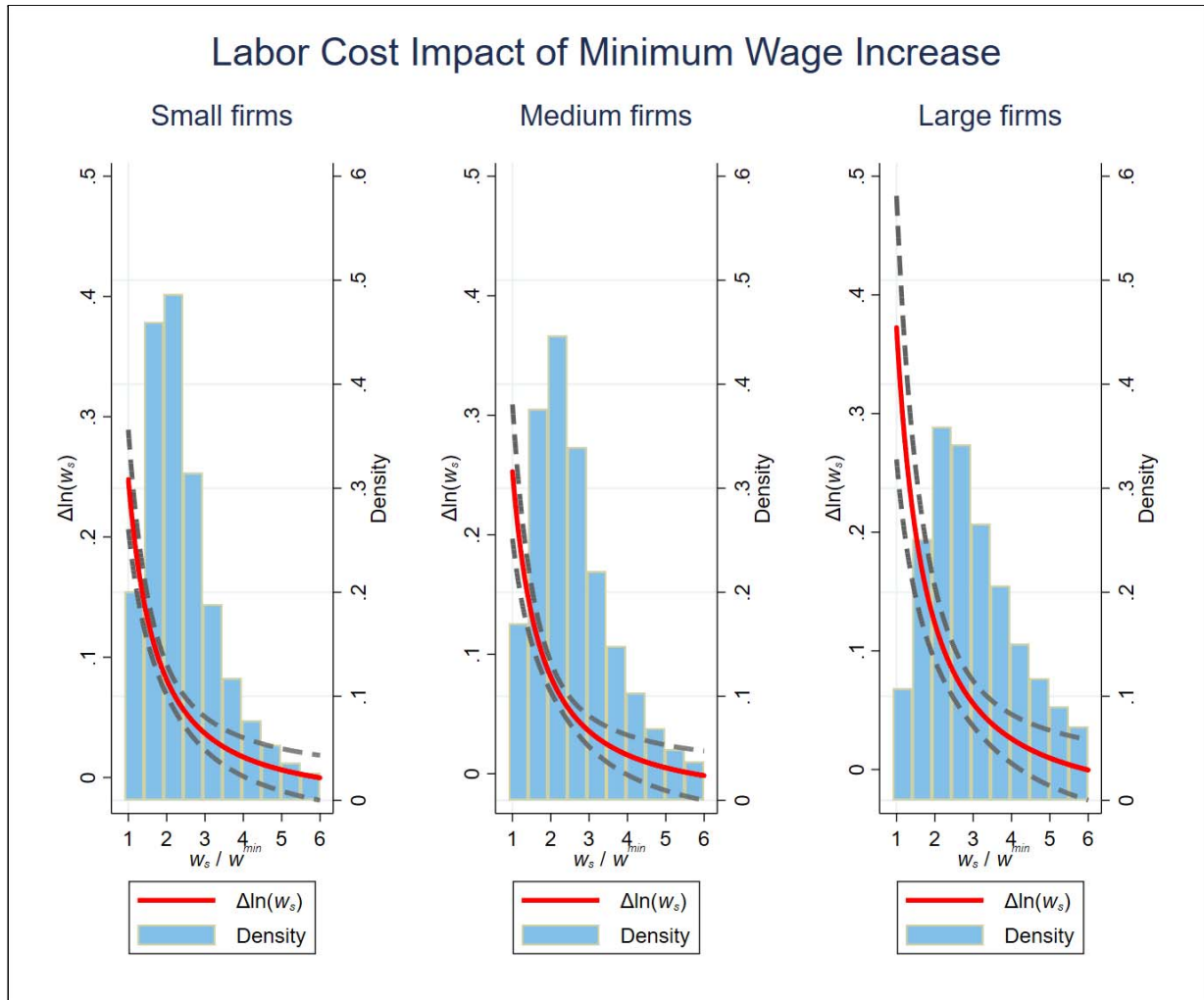


Figure 3: For small, medium, and large firms, we separately plot (on the left scale) the estimated (non-linear) average change in (log) firm wages $\Delta \ln w_s$ implied by a 22% minimum wage increase [$\Delta \ln(w^{\min}) = 0.2$] as a function of the ratio w_s/w^{\min} of the average firm wage w_s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

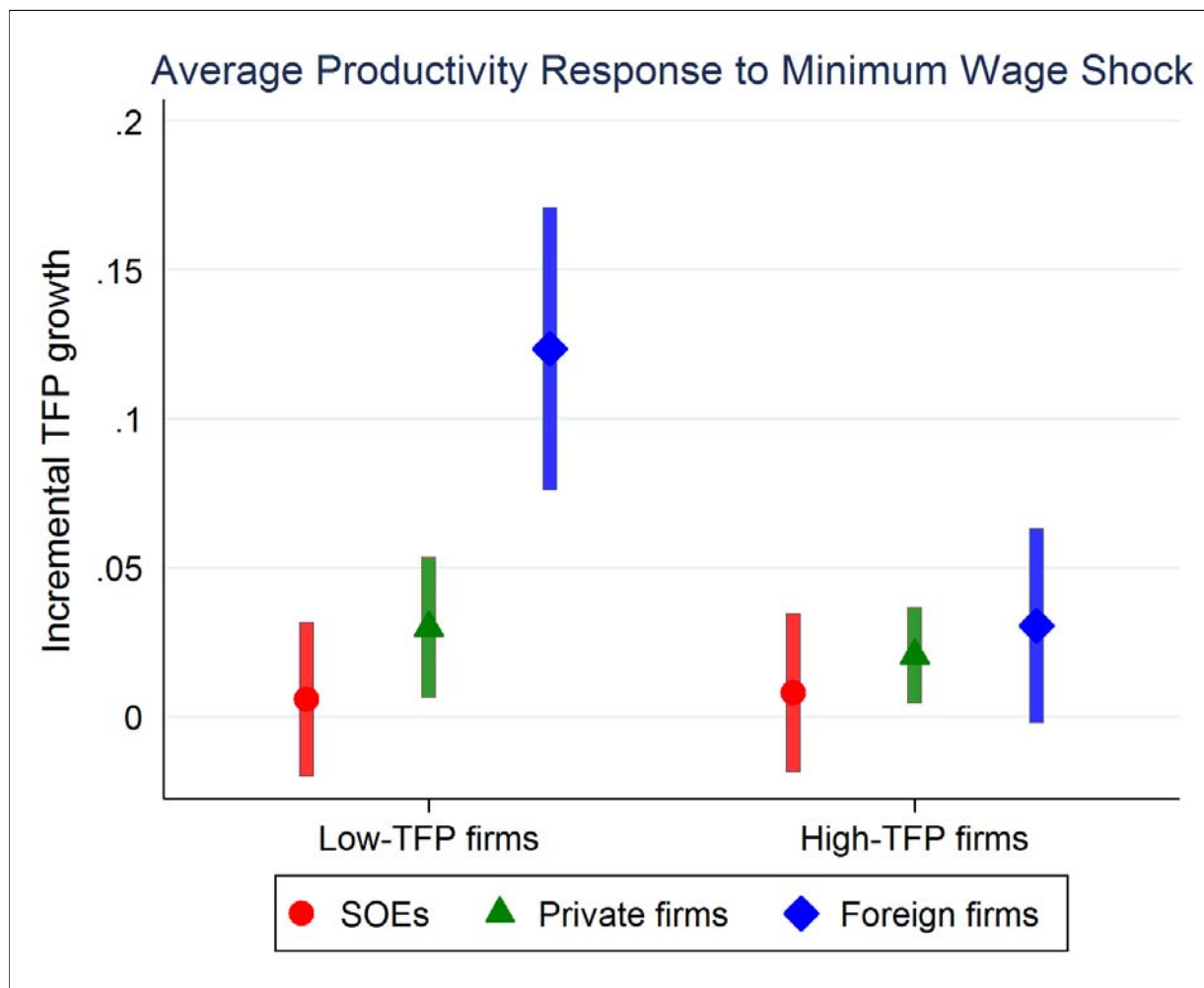


Figure 4: We plot the point estimates (and a two-sided bar of two standard deviations) for the incremental TFP growth resulting from a minimum wage shock of $IF_s \times \Delta \ln w^{\min} = 0.102$ for firms of different ownership type (SOEs, Private firms, Foreign firms) and below and above median TFP (Low-TFP firms versus High-TFP firms). The value of 0.102 is obtained for a 22% [$\Delta \ln w^{\min} = 0.2$] minimum wage increase and a comparison 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.

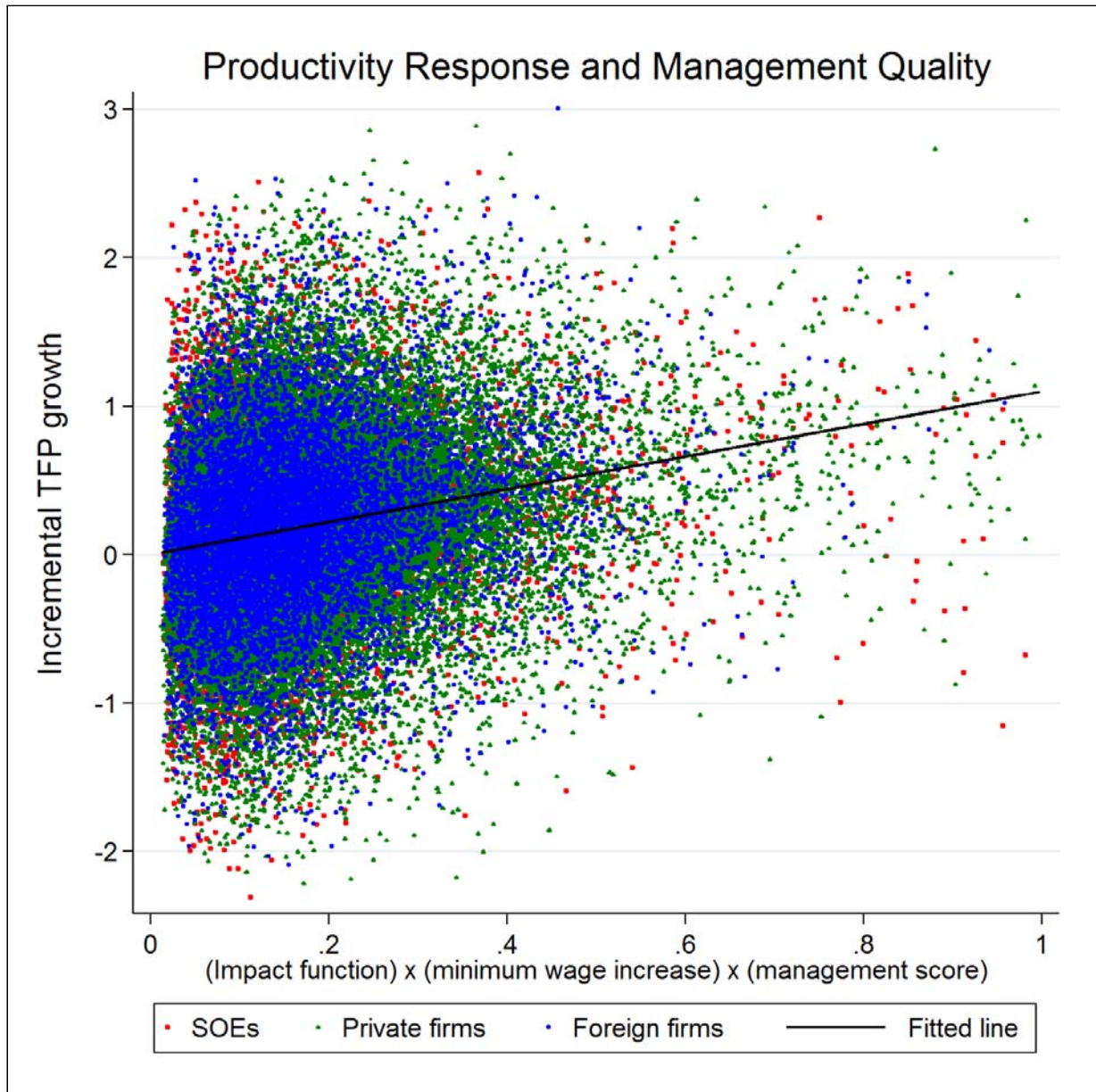


Figure 5: The residual plot based on Table 6, Column (5), shows the incremental TFP growth for low-TFP firms (i.e. firms below the median TFP level at the start of the sample) as a function of the triple interaction term $IF_s \times \Delta \ln w^{\min} \times Mgmt_Score$, where the impact function IF_s 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: Minimum 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								
$\Delta \ln(K/N)$	1,192,144	0.091	0.482	0.908	6.304	-0.373	0.011	0.667
$\Delta \ln(Y)$	1,192,144	0.175	0.630	-0.056	4.387	-0.566	0.173	0.922
$\Delta \ln(N)$	1,192,144	0.028	0.302	0.301	6.197	-0.288	0.000	0.372
$\Delta \ln(K)$	1,192,144	0.119	0.434	1.672	8.947	-0.125	-0.010	0.623
$\Delta \ln(A1)$	1,192,144	0.123	0.627	-0.081	4.201	-0.631	0.128	0.870
$\Delta \ln(A2)$	1,192,144	0.125	0.623	-0.068	4.214	-0.622	0.128	0.869
$IF_s \times \Delta \ln w^{\min}$	1,192,144	0.038	0.040	5.170	86.144	0.004	0.029	0.080
$\Delta \ln w^{\min}$	1,192,144	0.110	0.072	0.759	4.057	0.019	0.102	0.211
IF_s	1,192,144	0.361	0.277	4.774	51.573	0.119	0.311	0.629
w_s/w^{\min}	1,192,144	2.900	1.844	3.065	19.067	1.423	2.394	4.878
$IF_s \times \Delta \ln w^{\min} \times Mgmt_Score$	1,192,144	0.090	0.094	5.032	82.937	0.010	0.070	0.187
$Mgmt_Score$	1,192,144	2.392	0.197	0.640	3.657	2.166	2.367	2.658
Panel C: Exporting firms								
$\Delta \ln Exp_Value$	240,191	0.241	1.094	0.525	14.754	-0.667	0.169	1.275
$\Delta \ln Exp_Volume$	232,781	0.309	1.169	1.397	14.544	-0.635	0.156	1.474
$\Delta \ln Exp_Price$	232,781	-0.073	0.691	-4.478	54.800	-0.447	0.015	0.310

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 $IF_s(k) = (w_s/w^{\min})^{-k}$ 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 Δw^{\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 Δw_s (1)	FE $\Delta \ln w_s$ (2)	FE $\Delta \ln w_s$ (3)	NLLS Δw_s (4)	FE $\Delta \ln w_s$ (5)	FE $\Delta \ln w_s$ (6)	NLLS Δw_s (7)	FE $\Delta \ln w_s$ (8)	FE $\Delta \ln w_s$ (9)
k	0.373 (0.012)***	$k+1$ fixed	$k+1$ fixed	0.396 (0.019)***	$k+1$ fixed	$k+1$ fixed	0.361 (0.050)***	$k+1$ fixed	$k+1$ fixed
$IF_s(k) \times \Delta w^{\min}$	13.114 (0.412)***			11.871 (0.565)***			12.834 (1.714)***		
$IF_s(k)$	4.196 (0.046)***			4.172 (0.078)***			4.340 (0.252)***		
Δw^{\min}	-9.698 (0.392)***			-8.253 (0.529)***			-8.175 (1.607)***		
$IF_s(k+1) \times \Delta \ln w^{\min}$		0.771 (0.102)*** [0.100]***	1.923 (0.206)*** [0.212]***		0.550 (0.118)*** [0.123]***	1.864 (0.241)*** [0.272]***		0.886 (0.186)*** [0.223]***	2.653 (0.363)*** [0.459]***
$IF(k+1)$		0.684 (0.012)*** [0.028]***	1.262 (0.027)*** [0.083]***		0.662 (0.016)*** [0.029]***	1.164 (0.037)*** [0.088]***		0.646 (0.029)*** [0.047]***	1.350 (0.075)*** [0.174]***
$\Delta \ln w^{\min}$		0.072 (0.051) [0.046]	-0.166 (0.077)** [0.082]**		0.101 (0.047)** [0.048]**	-0.163 (0.077)** [0.090]*		0.051 (0.068) [0.077]	-0.234 (0.097)** [0.115]**
Ind. \times Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	682, 933	682, 933	600, 147	242, 611	242, 611	215, 241	38, 519	38, 519	35, 108

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

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

where $\mu_{Ind \times Year}$ represents a set of interacted industry and year fixed effects. Column (1) features 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 $IF_s(k+1) = (w_s/w^{\min})^{-(k+1)}$ 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 $k+1 = 1.373, 1.396,$ and 1.361 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. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms					SOEs	Foreign	Exporters
	LSDV (1)	LSDV (2)	DGMM (3)	LSDV (4)	LSDV (5)	LSDV (6)	LSDV (7)	LSDV (8)
$\Delta \ln(K/N)_{s,t-1}$			-0.080 (0.002)***					
$IF_s \times \Delta \ln w^{\min}$	0.356 (0.046)*** [0.053]***	0.346 (0.046)*** [0.052]***	0.333 (0.046)*** [0.050]***			0.105 (0.064) [0.067]	0.644 (0.101)*** [0.119]***	0.681 (0.103)*** [0.120]***
$IF_s \times \Delta \ln w^{\min} \times D_SOE$				0.108 (0.064)* [0.066]				
$IF_s \times \Delta \ln w^{\min} \times D_private$				0.344 (0.056)*** [0.061]***				
$IF_s \times \Delta \ln w^{\min} \times D_foreign$				0.637 (0.101)*** [0.117]***				
$IF_s \times \Delta \ln w^{\min} \times D_low\ TFP$					0.359 (0.060)*** [0.065]***			
$IF_s \times \Delta \ln w^{\min} \times D_high\ TFP$					0.330 (0.055)*** [0.063]***			
$\Delta \ln w^{\min}$	-0.059 (0.024)**	-0.052 (0.024)**	-0.063 (0.024)***			-0.019 (0.024)	-0.122 (0.041)***	-0.128 (0.041)***
IF_s	0.151 (0.006)***	0.154 (0.006)***	0.143 (0.006)***			0.132 (0.011)***	0.143 (0.012)***	0.163 (0.012)***
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. \times Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1, 101, 976	1, 101, 976	624, 730	1, 101, 976	1, 101, 976	93, 866	244, 558	221, 100
AR(1)			-144.02					
AR(2)			0.35					

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

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

where $Z_s = Y_s, N_s, K_s, \Pi_s$ 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. 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 (1)	LSDV (2)	LSDV (3)	LSDV (4)	LSDV (5)	LSDV (6)	LSDV (7)	LSDV (8)	LSDV (9)
$IF_s \times \Delta \ln w^{\min}$	0.171 (0.053)*** [0.056]***			-0.193 (0.033)*** [0.042]***			0.153 (0.038)*** [0.041]***		
$IF_s \times \Delta \ln w^{\min} \times D_{-SOE}$		-0.045 (0.092) [0.094]			-0.115 (0.050)** [0.053]**			-0.007 (0.046) [0.047]	
$IF_s \times \Delta \ln w^{\min} \times D_{-private}$		0.172 (0.063)*** [0.062]***			-0.181 (0.040)*** [0.049]***			0.164 (0.047)*** [0.048]***	
$IF_s \times \Delta \ln w^{\min} \times D_{-foreign}$		0.498 (0.148)*** [0.168]***			-0.367 (0.074)*** [0.088]***			0.270 (0.080)*** [0.089]***	
$IF_s \times \Delta \ln w^{\min} \times D_{-low TFP}$			0.220 (0.082)*** [0.089]***			-0.275 (0.045)*** [0.049]***			0.084 (0.044)* [0.046]*
$IF_s \times \Delta \ln w^{\min} \times D_{-high TFP}$			0.173 (0.062)*** [0.063]***			-0.145 (0.038)*** [0.048]***			0.184 (0.048)*** [0.053]***
$\Delta \ln w^{\min}$	-0.041 (0.031)			0.032 (0.016)**			-0.020 (0.022)		
IF_s	0.119 (0.007)***			-0.148 (0.005)***			0.006 (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, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976	1, 101, 976

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

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

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. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level respectively.

	All firms					SOEs	Foreign	Exporters
	LSDV (1)	LSDV (2)	DGMM (3)	LSDV (4)	LSDV (5)	LSDV (6)	LSDV (7)	LSDV (8)
$\Delta \ln A1_{s,t-1}$			-0.156 (0.003)***					
$IF_s \times \Delta \ln w^{\min}$	0.272 (0.064)*** [0.073]***	0.261 (0.063)*** [0.073]***	0.234 (0.061)*** [0.071]***			0.026 (0.104) [0.110]	0.690 (0.170)*** [0.213]***	0.806 (0.156)*** [0.200]***
$IF_s \times \Delta \ln w^{\min} \times D_SOE$				0.043 (0.098) [0.105]				
$IF_s \times \Delta \ln w^{\min} \times D_private$				0.241 (0.074)*** [0.078]***				
$IF_s \times \Delta \ln w^{\min} \times D_foreign$				0.723 (0.171)*** [0.211]***				
$IF_s \times \Delta \ln w^{\min} \times D_low\ TFP$					0.409 (0.097)*** [0.110]***			
$IF_s \times \Delta \ln w^{\min} \times D_high\ TFP$					0.209 (0.069)*** [0.076]***			
$\Delta \ln w^{\min}$	-0.076 (0.033)**	-0.052 (0.033)	-0.032 (0.032)			0.067 (0.043)	-0.064 (0.072)	-0.099 (0.067)
IF_s	0.222 (0.008)***	0.224 (0.008)***	0.165 (0.008)***			0.166 (0.017)***	0.243 (0.020)***	0.232 (0.019)***
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 \times Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1, 101, 976	1, 101, 976	615, 992	1, 101, 976	1, 101, 976	93, 866	244, 558	221, 100
$AR(1)$			-129.73					
$AR(2)$			-4.19					

Table 6: Productivity Effect by Management Practice

We regress the management score of 548 Chinese firms in 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 (1)	LSDV (2)	DGMM (3)	LSDV (4)	LSDV (5)	DGMM (6)	LSDV (7)	LSDV (8)	DGMM (9)
$\Delta \ln A1_{s,t-1}$			-0.156 (0.003)***			-0.172 (0.003)***			-0.140 (0.003)***
$IF_s \times \Delta \ln w^{\min} \times Mgmt_Score$	0.412 (0.265) [0.291]	0.488 (0.260)* [0.292]*	0.518 (0.250)** [0.290]*	1.065 (0.457)** [0.505]**	1.102 (0.451)** [0.508]**	1.368 (0.469)*** [0.521]***	-0.065 (0.301) [0.315]	0.079 (0.295) [0.309]	0.034 (0.271) [0.313]
$\Delta \ln w^{\min} \times Mgmt_Score$	0.060 (0.113) [0.126]	0.046 (0.112) [0.124]	-0.056 (0.109) [0.125]	-0.369 (0.154)** [0.174]**	-0.341 (0.153)** [0.171]**	-0.311 (0.155)** [0.165]*	0.379 (0.136)*** [0.140]***	0.315 (0.134)** [0.139]**	0.086 (0.129) [0.150]
$IF_s \times Mgmt_Score$	0.054 (0.034) [0.044]	0.047 (0.034) [0.044]	0.028 (0.031) [0.036]	-0.063 (0.055) [0.063]	-0.069 (0.054) [0.063]	-0.166 (0.051)*** [0.062]***	0.116 (0.038)*** [0.045]***	0.104 (0.037)*** [0.045]***	0.102 (0.034)*** [0.039]***
$Mgmt_Score$	-0.213 (0.031)*** [0.041]***	-0.168 (0.031)*** [0.043]***	-0.090 (0.029)*** [0.043]**	0.263 (0.036)*** [0.044]***	0.285 (0.036)*** [0.044]***	0.135 (0.034)*** [0.044]***	-0.473 (0.037)*** [0.048]***	-0.406 (0.038)*** [0.050]***	-0.270 (0.036)*** [0.054]***
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 \times Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	1, 101, 976	1, 101, 976	638, 582	524, 209	524, 203	317, 058	577, 767	577, 767	321, 524
AR(1)			-129.85			-108.36			-122.39
AR(2)			-4.23			-6.44			5.20

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. 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 (1)	LSDV (2)	DGMM (3)	LSDV (4)	LSDV (5)	DGMM (6)	LSDV (7)	LSDV (8)	DGMM (9)
$\Delta \ln Exp_XX_{s,t-1}$			-0.096 (0.007)***			-0.058 (0.006)***			-0.049 (0.007)***
$IF_s \times \Delta \ln w^{\min}$	0.294 (0.182) [0.194]			0.232 (0.196) [0.222]			-0.009 (0.099) [0.104]		
$IF_s \times \Delta \ln w^{\min} \times D_SOE$		0.650 (1.084) [1.102]	-1.151 (1.156) [1.254]		0.494 (1.035) [1.023]	-1.064 (1.220) [1.283]		-0.056 (0.608) [0.564]	0.116 (0.701) [0.687]
$IF_s \times \Delta \ln w^{\min} \times D_private$		-0.028 (0.324) [0.333]	0.627 (0.386) [0.432]		-0.248 (0.345) [0.368]	0.351 (0.398) [0.419]		0.227 (0.186) [0.198]	0.121 (0.243) [0.216]
$IF_s \times \Delta \ln w^{\min} \times D_foreign$		0.547 (0.214)** [0.213]**	0.360 (0.203)* [0.186]*		0.566 (0.233)** [0.232]**	0.485 (0.225)** [0.235]**		-0.129 (0.117) [0.116]	-0.194 (0.142) [0.146]
All other (interaction) terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE \times Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221, 123	221, 100	112, 837	213, 577	213, 553	107, 388	213, 577	213, 553	107, 388
AR(1)			-32.86			-39.10			-27.51
AR(2)			-0.17			0.54			-0.20