The Division of Unexpected Revenue Shocks^{*}

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October 2021

Abstract

We exploit gaps between observed and recently forecasted GDP growth in export destinations to estimate the effects of unexpected revenue shocks on worker compensation. Using employer-employee panel data, we find that these unexpected demand shocks are partly transmitted to workers in the form of higher average wages, especially close to the top of the within-firm wage distribution. The unequal average distribution of rents is mainly driven by wage effects in firms managed by high-skilled managers, and by changes in overtime and other pay. This suggests that different types of managers implement different pay systems in the firm.

Keywords: Unexpected revenue shocks, firm performance, exports, rent sharing, managers. JEL Classification: J2, J6, F16, F66

^{*}The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, those of the Executive Directors of the World Bank, or those of the governments they represent. Bastos is also affiliated with the CEPR and REM. We remain responsible for any errors.

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1 Introduction

Suppose that a firm experiences an unexpected revenue shock. Does it choose to invest or hire more workers? Does it alter workers' compensation, and if so mainly through base wages or other components of pay? How are these decisions shaped by the attributes of top executives? Naturally, appreciation is growing in a number of fields—macroeconomics, labor, industrial organization, as well as international trade—for careful empirical work seeking to improve our understanding of these issues.¹ However, research has faced two important challenges. First, it has been difficult to quantify in a systematic but precise way the unexpected component of revenue shocks at the firm-level, while distinguishing it from anticipated changes in market conditions. Second, studying these questions jointly—and thus providing a comprehensive analysis of intertwined decisions at the firm-level—requires an unusually rich collection of longitudinal data on firms, workers and the components of compensation.

In this paper, we estimate the effects of unexpected revenue shocks on firm performance and worker compensation. We propose a new methodology to identify the unexpected component of demand shocks at the firm-level, exploiting forecast errors in the GDP growth of export markets. In each destination, the unexpected component of demand shocks is measured as the difference between the GDP growth actually observed and recent forecasts of the International Monetary Fund. We then aggregate these shocks at the firm-year level, weighting by the initial share of destinations in firms' total sales. Since firms initially served different destinations to a varying degree, they were differentially exposed to these unexpected demand shocks across markets.

The empirical analysis draws on an unusually rich collection of data sets for the population of private sector firms operating in Portugal during 2006-2018. We combine a yearly firm census with information on export transactions and employer-employee panel data. We also use an auxiliary data set from a management survey for 2016, covering a subset of these firms. The employer-employee data allow us to distinguish between effects on each of the various components of worker compensation, including base wages, overtime pay, and other regular and irregular components of compensation. In addition, the information on schooling and detailed occupation makes it possible to examine heterogeneity in the wage effects of revenue shocks across workers in different positions of the wage distribution, and how these effects are shaped by the skills of top executives.

In the empirical analysis, we find that unexpected revenue shocks induce firms to increase

¹Recent contributions to this literature, reviewed in more detail below, include Card, Cardoso, Heining, and Kline (2018), Frías, Kaplan, Verhoogen, and Alfaro-Serrano (2018) Kline, Petkova, Williams, and Zidar (2019), Aghion, Akcigit, Hyytinen, and Toivanen (2018) and Grigsby and Yildirmaz (2021).

sales, employment, investment and average wages. Using employer-employee panel data, we find that firm revenue windfalls, in the form of unexpected demand shocks, are partly transmitted to workers in the form of higher average wages, but in a highly unequal way, with most of the wage increases occurring close to the top of the within-firm wage distribution. We find little evidence of adjustments in the skill composition of the workforce, as quantified either by the share of workers with a degree or estimated individual effects.

These results suggest that firms tend to share the unexpected changes in revenue with their workers. Several (non-mutually exclusive) mechanisms could be at play. First, rent sharing could be driven by worker bargaining power, either at the individual-level or through labor unions. Second, it could result from explicit profit-sharing arrangements, for example in the form of performance-based pay contracts (Lazear, 1986, 2000). Third, wage determination might partly result from firms' incentives to induce the desired amount of effort from its labor force, in line with the *fair wage* hypothesis of Akerlof and Yellen (1990). Finally, rent sharing could be driven by monopsony power in the labor market, for example because of market concentration on the demand side or heterogeneous job preferences on the supply side (Manning, 2021).

Although each of these mechanisms can contribute to explain our findings, a second set of key results suggests that some mechanisms appear to be more important than others. We find that the unequal average distribution of rents following an unexpected revenue windfall is mainly driven by wage effects in firms managed by high-skilled managers. This suggests that different types of managers might be implementing different pay systems in the firm. In particular, high-skill managers might be more likely to adopt performance-based pay for workers close to the top end of the wage distribution, who are more likely to have a direct impact on the firm's performance (Juhn, McCue, Monti, and Pierce, 2018). Interestingly, we further find that the unequal sharing of rents within the firm is mainly driven by changes in overtime pay and other pay, with the unexpected revenue windfall raising these two wage components mainly for high earners in the firm. These findings suggests that managerial skill is, at least in part, associated with the adoption of performance-based pay, which would show up in these wage components.

Related literature In addition to the literature mentioned above, this paper relates to several strands of existing research. A large body of literature in labor economics uses detailed employer-employee panel data to quantify and explain wage differentials across firms.² In a recent review of this literature, Card, Cardoso, Heining, and Kline (2018) conclude that more research is needed applying (quasi)-experimental research designs that convincingly tease out the

²Influential contributions include, among many others, Abowd and Margolis (1999) (henceforth AKM), Card, Heining, and Kline (2013), Card, Cardoso, and Kline (2015) and Song, Price, Guvenen, Bloom, and von Wachter (2019).

mechanisms through which firm shocks are transmitted to workers. A few recent papers have contributed to fill this gap. Exploiting an unexpected devaluation of the Mexican currency, Frías, Kaplan, Verhoogen, and Alfaro-Serrano (2018) carefully estimate how differential export shocks across firms impact wage premia and worker composition.³ The results reveal that exports have a significant positive effect on wage premia, and that the effect on wage premia accounts for essentially all of the medium-term effect of exporting on plant-average wages.⁴ Kline, Petkova, Williams, and Zidar (2019) estimate the effects of innovation on rent-sharing using employer-employee data and rich patent information for the United States. Under the identifying assumption that the U.S. Patent Office's initial decision on a patent application is as good as random (conditional on observable attributes of the application and the firm), the authors find that each patent-induced additional dollar of operating surplus yields a 29-cent rise in a firm's wage bill. Also focusing on patents, but using Finish data and a matching estimator, Aghion, Akcigit, Hyytinen, and Toivanen (2018) find that patents are positively associated with earnings of the co-workers of inventors.

Our paper makes several contributions to this literature. First, the employer-employee data we use make it possible to examine effects of unexpected export shocks on observable worker attributes, and to distinguish between impacts on the various components of worker compensation (bases wages, overtime and other components of pay). Recent work by Grigsby and Yildirmaz (2021) convincingly argues that this distinction is important for examining and understanding the extent of wage rigidity over the business cycle.⁵ Second, we exploit the role of top managers' skills—which we show are correlated with management practices observed in data—in shaping these effects. Although a growing body of evidence reveals that manager attributes are important for management practices and firm performance (Bertrand and Mullainathan, 2003; Bertrand and Schoar, 2003; Bastos and Monteiro, 2011; Bender, Bloom, Card, Van-Reenen, and Wolter, 2018), there is little evidence on whether and how managers matter for how exogenous firm shocks are transmitted to workers. Finally, the methodology we propose for identifying firm-level revenue windfalls has some advantages relative to the shocks previously exploited. Although exchange rate movements and innovations leading to patents are difficult to forecast,

³The broader literature on firm and labor market responses to exchange rate movements includes Revenga (1992), Bertrand (2004), Verhoogen (2008), Brambilla, Lederman, and Porto (2012), Amiti, Itskhoki, and Konings (2014) and Bastos, Silva, and Verhoogen (2018), among others.

⁴A related strand of work examines the relationship between exports and wages, but does not exploit quasiexperimental variation in exports, including Schank, Schnabel, and Wagner (2007), Munch and Skaksen (2008), Baumgarten (2013), Irarrazabal, Moxnes, and Ulltveit-Moe (2013), Macis and Schivardi (2016), Helpman, Itskhoki, Muendler, and Redding (2017).

⁵Using administrative payroll data from the largest U.S. payroll processing company, they provide descriptive evidence that firms use base wages to cyclically adjust the marginal cost of their workers, although about one third of workers receive no base wage change year over year.

variation over time is likely to reflect in part economic fundamentals and policy choices. These developments can be monitored and analysed by firms, which may therefore partly respond in anticipation.⁶ Identifying the effects of unexpected exchange rate movements is further complicated by the fact that they are subject to incomplete pass-through, which may be influenced by the currency in which trade transactions are denominated and vary across firms and markets (Amiti, Itskhoki, and Konings, 2014; Gopinath, Boz, Diez, Gourinchas, and Plagborg-Moller, 2020).⁷ Unexpected GDP shocks in destinations are arguably less subject to this concern.⁸

Our paper further speaks to a recent strand of work highlighting the role of internationally active firms in the international transmission of business cycles. Using French firm-level data, di Giovanni, Levchenko, and Mejean (2018) show that trade linkages with a foreign country are associated with a significantly higher correlation between a firm and that foreign country, which has significant macro implications. In related work, di Giovanni, Levchenko, and Mejean (2020) document that larger French firms are significantly more sensitive to foreign GDP growth. Using a quantitative model, they find that this granularity accounts for 40 to 85% of the impact of foreign fluctuations on French GDP. Focusing on exporting firms, we contribute to this literature by estimating the response of firm-level sales, employment, investment and wages to both expected and unexpected fluctuations in foreign GDP growth. In addition, we use employer-employee data to estimate how each of these shocks impact the different components of worker compensation within and across heterogeneous exporters. As Grigsby and Yildirmaz (2021) emphasize, measuring this nominal wage adjustment in micro data is key for disciplining macroeconomic theories of nominal wage rigidity.

Roadmap The paper is organized as follows. Section 2 describes the data, before Section 3 presents the method for identifying the unexpected component of demand shocks at the firmlevel. Section 4 describes the econometric model, while 5 reports the corresponding empirical results. Section 6 concludes the paper.

⁶Since there are no official forecasts for bilateral exchange rates, it is often difficult to isolate the unexpected component of exchange rate shocks.

⁷Furthermore, exchange rate movements may impact not only firm revenues in export destinations, but also the prices of materials, components and technologies sourced from those markets (which may complement or replace workers). It has been difficult to fully distinguish between these effects. Unexpected demand shocks in destinations are arguably more likely to impact firm performance primarily through exports.

⁸In an important contribution, Hummels, Jorgensen, Munch, and Xiang (2014) examine effects of offshoring and external demand shocks on wages, using employer-employee data from Denmark. Identification of demand shocks exploits variation in firm-specific weighted averages of imports of particular goods by the firm's trading partners, using the firm's initial shares as weights. We innovate by isolating the unexpected (and idiosyncratic) component of export shocks in destinations. In addition, we separately identify effects on the different components of pay, show that wage gains accrue mainly to top earners, and to firms initially led by highly skilled top executives.

2 Data

The empirical analysis in this paper combines and examines several sources of panel data from Portugal spanning the period 2006-2018. We provide a brief description of each data source in this section and give further details in Appendix A.3.

Employer-employee data: *Quadros de Pessoal (QP)* [Personnel Records] is a high-quality compulsory census run by the Ministry of Employment covering the population of firms with wage earners in manufacturing and services. Each firm is required by law to provide information on an annual basis about its characteristics and those of each individual that comprises its workforce. Firm-level information includes annual sales, number of employees, industry code, geographical location, date of constitution and share of capital that is foreign-owned. The set of worker characteristics includes wages (monthly base wage, overtime pay, and other components of pay), gender, age, schooling, date of starting, detailed occupation and hours worked. A worker may also be matched to the firm in which he is employed. Extensive checks have been performed to guarantee the accuracy of worker and firm data. After these checks, we kept for analysis full-time wage earners working at least 100 hours a week, and aged between 20 and 60 years old.

Firm census: Using common unique firm identifiers, we supplement the firm-year data from QP with information from *Sistema de Contas Integradas das Empresas (SCIE)* [Enterprise Integrated Accounts System], a yearly census of firms run by National Statistics Institute (INE). The main objective of SCIE is to characterise the economic and financial behaviour of firms. This data set includes information on total sales, investment, employment, value added, wage bill, industry, location, among several other variables.

International trade statistics: We merge the above data sets with yearly data on firms' export transactions from *Estatsticas do Comrcio Internacional (ECI)* [Foreign Trade Statistics] from INE. This is the country's official information source on imports and exports. It comprises the export flows of virtually all exporting firms, and provides detailed information on the product exported, the destination market, and the value and quantity exported. Export values in these data are free-on-board, thus excluding any duties or shipping charges.

Management practices survey: We further use data from *Inqurito s Pricas de Gesto* (*IPG*) [Management Practices Survey] for 2016. IPG is a non-periodical survey conducted by INE, which collects information on the perceptions of top executives about the management practices of their firms. The 2016 survey was the first and only of its kind collected in Portugal. It seeks to evaluate the importance of management practices for firm productivity, as well as

other key indicators that make it possible to evaluate differences in productivity between Portuguese firms. IPG employed a stratified sample of firms operating in Portugal covering the whole non-financial private sector in 2016, excluding micro firms (with less than five employees). The sample is representative by sector (20 sectors corresponding of aggregations of the 2-digit level of the CAE), firm size and age, as well as belonging (or not) to a conglomerate. The IPG survey includes questions seeking to evaluate management practices in three main areas: (1) Strategy, monitoring and information; (2) Human Resources; and (3) Management and social responsibility systems. We selected 18 variables that are closely related to those adopted in Bloom and Reenen (2007). Following their approach, our measure of management quality was constructed by z-scoring (normalising to mean 0, standard deviation 1) the 18 individual questions in IPG, taking averages, and then z-scoring the average. This process yields a management practice score with mean 0 and standard deviation 1.

Actual and forecasted GDP growth: We further use yearly information on actual and recently forecasted GDP growth from the World Economic Outlook (WEO) of the International Monetary Fund (IMF). WEO is usually published twice a year (in April and September/October). It presents IMF staff economists' analyses of global economic developments during the near and medium term. Every April and October, the WEO provides year-ahead and current-year GDP growth forecasts. We refer to the year for which the forecast is being made as the target year. Forecasts made in the the Fall WEO before the target year are called year-ahead forecasts and those made during the Spring target year are called current-year forecasts. During our sample period, forecast data are available for 195 countries. After merging these data with ECI we were left with 174 destinations, which account for 99.7% of all exports in 2006. Table A2 reports the export shares to the main destinations in 2006, both in the full ECI data and in the estimation sample.

3 Methodology for identifying unexpected demand shocks

In this section, we propose a new methodology to identify the unexpected component of demand shocks at the firm-level, which exploits forecast errors in the GDP growth of export markets. In each destination, the unexpected component of demand shocks is measured as the difference between the GDP growth actually observed and the current-year growth forecast for that country published in the Spring edition of the World Economic Outlook of the International Monetary Fund. Specifically, the forecast error for a destination-year is defined as:

$$FE_{dt} = G_{dt} - FG_{dt},\tag{1}$$

where FE_{dt} denotes the forecast error for destination d in year t, G_{dt} denotes the GDP growth rate of destination d in year t and FG_{dt} denotes the current-year growth forecast for country d in year t. We then aggregate these destination-year forecast errors at the firm-year level, weighting by the share of destinations in total sales of firm i in the initial year:

$$WFE_{it} = \sum_{d=0}^{D} s_{di0} FE_{dt},$$
(2)

where s_{d0} is the share of exports to destination d in total sales of firm i in 2006 (the first year of our data) and D is the set of destinations for which data on growth forecasts are available. Since firms initially served different destinations to a varying degree, they were differentially exposed to these unexpected demand shocks across markets. Using the same weights, we also aggregate the forecast growth (WFG) at the firm-year level.

4 Econometric method

We now describe the econometric strategy for examining the effects of unexpected revenue shocks on firm performance and worker compensation. Our baseline specification is:

$$\Delta Y_{ip} = \alpha \Delta W F E_{ip} + \beta \Delta W F G_{ip} + \gamma_{jp} + \tau_{rp} + \epsilon_{ip}, \tag{3}$$

where Y_{ip} denotes the log of the outcome variable of interest in firm *i* in period *p*; WFE_{ip} is the weighted forecast error in firm *i* in period *p*; WFG_{ip} is the weighted forecast growth in firm *i* in period *p*; γ_{jp} denotes an industry-period effect; τ_{rp} denotes a region-period effect; and ϵ_{ip} is the error term. For all variables, we take 3-year period averages of the corresponding firm-year variables. Furthermore, the period definition of all the independent variables is lagged one year compared to the period definition of the dependent variable Y.⁹ This makes it possible to capture potential lagged responses to unexpected shocks. The Δ operator denotes the linear change of a variable between each period *p* and period p - 1 throughout the paper. The industry-period effects absorb common shocks to all firms in an industry in each period, while the region-period

⁹If period p is defined for the independent variables as the three years from t to t + 2, the dependent variable Y_{ip} measures the (log of the) outcome variable of interest averaged over the years t + 1 to t + 3.

effects capture the impacts of common shocks across firms operating in the same region in a given period. We report standard errors clustered by firm.

5 Results

5.1 Summary statistics

Before turning to the econometric analysis, we report descriptive statistics on several variables underlying our empirical strategy. Our firm-level baseline estimation sample is composed of manufacturing firms that exported in 2006, and for which it is possible to link information from all the data sets described above (except the IPG survey, which is available only for a subset of firms in 2016). Table 1 reports summary statistics on firms from the estimation sample, both in levels and in changes. These statistics reveal that there exists considerable variation across firms and over time with regard to the weighted average of actual and forecast growth. Table A1 in the Appendix provides summary statistics on firms in the estimation sample for each 3-year period considered in the econometric analysis. Once again, these descriptive statistics show considerable variation across firms in the main variables of interest, both within and across periods.

[Table 1 here]

Table A2 in the Appendix reports key moments on the distribution of export destinations of Portuguese manufacturing firms in 2006, both in the full customs data and in our estimation sample. The main export destinations are other EU member states that are part of the eurozone (Spain, Germany, France), but also include countries outside the eurozone and/or the EU, notably the United Kingdom, United States, Angola and Singapore. For all destinations, export shares in the estimation sample are remarkably similar to those in the full customs data.

Figure A1 in the Appendix shows the variation of forecasted and actual GDP growth in each of the top 18 destinations for Portuguese exports. We observe significant variation across destinations with regard to both these variables. Since firms initially served different destinations to a varying degree, they were differentially exposed to these unexpected demand shocks across markets.

Figure 1 shows that there exists significant variation across firms in the estimation sample with regard to weighted actual and forecast growth. The range of forecast and actual growth is often greater than 10 percentage points, which is considerably higher than the averages for both these variables. The range of forecast growth is especially wide (and considerably larger than that of actual growth) in the initial years of the sample period, but remains sizeable over the whole period.

[Figure 1 here]

5.2 Average effects on firm performance and worker compensation

We now turn to the main focus of the empirical analysis: the impacts of unexpected revenue shocks on firm performance and worker compensation. Table 2 reports the point estimates on the effects of the weighted forecast error and weighted forecast growth on various measures of firm performance and average labor costs, using data from SCIE. Columns (1) and (2) reveal that unexpected revenue shocks in export destinations lead to increased sales and exports, with the latter showing stronger responses than the former. The stronger effects on exports would be expected given the source of variation we are exploiting: unforeseen growth shocks in export destinations. We also observe that the magnitude of the effects of the forecast error on both exports and sales is slightly larger than that of the forecast growth. We take these results as reassuring confirmation that our strategy for identifying unexpected demand shocks is valid. Columns (3) to (7) also show significant effects on investment (in both tangible and intangible assets), employment, value added and average labor costs. The effects of the weighted forecast error on investment in intangibles, employment and average labor costs are considerable stronger than those of the weighted forecast growth.

[Table 2 here]

In Table 3, we use the employer-employee data to examine the effects on the various components of worker compensation and on the skill composition of the workforce. Regarding worker compensation, The total monthly wage consists of three components: *base wage, overtime pay*, and *other pay* (e.g., various types of bonuses). We also have information on the number of hours worked per month, which allows us to calculate the total hourly wage. We report effects on firm-level averages of each of these variables.

[Table 3 here]

The estimates in columns (1) and (2) indicate positive and significant effects of the forecast error on both monthly and hourly wages. Columns (3)-(4) show that this positive average effect is mainly driven by adjustments in average base wages and, to some extent, by changes in overtime pay. The *other pay* coefficient in column (5) also has a sizeable positive point estimate, though the effect on this residual wage component is not statistically significant. In line with the employment responses documented in Table 2, column (6) shows a positive impact on total hours worked. Finally, columns (7) and (8) do not show any significant impact on skill composition, as measured either by the share of workers with a degree or the average of person effects estimated through AKM models. The positive and significant effects on base wages, along with the absence of effects on worker composition, suggest that the unexpected increase in rents is partly shared with workers through permanent rises in their compensation.

5.3 The division of revenue shocks

We proceed by examining whether the division of rents inside the firm accrues disproportionally to some groups of the workforce. In particularly, we verify if the revenue shocks benefit mainly the firms' high earners, thereby contributing to increased intra-firm wage inequality, or if the rents are more evenly distributed among the entire workforce.

[Table 4 here]

In Table 4 we show the estimated effects of unexpected revenue shocks on the average monthly wages of high versus low earners within each firm, using three different earnings thresholds. These estimates display a very clear and consistent pattern. First, the estimated effect is consistently larger (and more significant) for the high earners than for the rest of the workforce. In fact, among workers outside the top 25 percent of the earnings distribution, the average wage effect is not significantly different from zero. Furthermore, the estimated wage effect for the high earners is monotonically increasing in magnitude (and statistical significance) as we move the high earner threshold further towards the top end of the distribution. This suggests that, on average, the division of rents caused by unexpected revenue shocks is highly unequal and strongly benefitting the firms' top earners.

5.4 The importance of managerial skill

We now examine if and how the distribution of rents generated by unexpected revenue shocks vary systematically with the skill-level of the firms' top managers (measured at the beginning of the sample period). The underlying assumption (which we explore and discuss below) is that differences in managerial skill is systematically linked with the adoption of different management practices, which in turn affect worker behaviour and effort. For management practices that are likely to interact with worker behaviour (e.g., monitoring, goal setting, and incentive schemes), it seems reasonable to assume that the effects of such practices depend on the characteristics of the workforce. Thus, we would expect that the adoption of different management practices is systematically related to differences in both the skill composition of the firm's workforce and the structure of its pay system. Indeed, a growing body of evidence suggests that the skills of top executives are important for management practices, employee selection and firm performance (Bertrand and Mullainathan, 2003; Bertrand and Schoar, 2003; Bastos and Monteiro, 2011; Bender, Bloom, Card, Van-Reenen, and Wolter, 2018). However, there is little evidence on whether and how managers matter for how exogenous firm shocks are transmitted to workers.

5.4.1 Measuring managerial practices and managerial skills

Following Bender, Bloom, Card, Van-Reenen, and Wolter (2018), we first use the 2016 management survey to compute firm-level management *z-scores*—an index of adoption of advanced management practices. We then link these data to the other data sets on workers and firms. This allows us to relate measured management quality to worker and firm observables, including worker pay at previous employers in 2011-2016, which we use to estimate worker effects in order to infer ability. The worker effects allow us to measure the quality of workers' skills at each plant as well as the relative quality of top managers versus other workers.

Table A3 in the Appendix provides descriptive statistics on worker and firm attributes for firms with management z-scores above and below the median. To proxy for worker ability, we consider estimates of individual effects from AKM models using data for the period 2011-2016. We use a similar approach to estimate managers' ability. Furthermore, we consider a direct measure of firm management skills, namely the share of a firm's managers holding a university degree. Managers are identified in two alternative ways. One approach is to identify managers directly by *occupational category* in the data (using the categories CEO and other top managers). Although allowing for more precise identification, the downside of this approach is a considerable loss of observations due to missing data. We therefore complement this approach by an alternative identification strategy whereby the *one percent highest earners* in the firm are classified as top managers.

The set of firm-level attributes is composed of firm size, the share of foreign and state capital, firm age, the percentage of female employees, export status and export share. The summary statistics reported in Table A3 reveal that firms with higher management z-scores tend to be larger, to have a greater share of foreign and privately-owned capital, and are slightly more likely to be exporters and tend to employ a larger share of female workers. Turning to worker and manager attributes, the statistics reveal that firms with above-median z-scores tend to have a higher share of workers and managers with a degree, as well as larger average estimates of employee and managers' ability (as revealed by person effects from AKM models). The relationship between z-scores and observable manager characteristics is further explored in Figure A2 in the Appendix. In this figure we show the distribution of z-scores across firms with high- and low-skilled managers, respectively, where the former (latter) are defined as firms with a share of managers with a degree above (below) the median. These distributions are shown when managers are identified according to occupational category (Panel A) and when managers are identified as the top one percent earners in the firm (Panel B). In both cases, we see that the z-score distribution of firms with high-skilled managers. This pattern is generally consistent with the evidence in Bender, Bloom, Card, Van-Reenen, and Wolter (2018) for Germany, and suggests that observed skills of top executives are systematically associated with advanced management practices.

5.4.2 Managerial skill and rent distribution

Having shown that management z-scores tend to be higher among firms with a greater share of highly-skilled top executives, we now examine whether and how managers matter for the distribution of rents created by exogenous demand shocks. To do so, we split our estimation sample according to whether the proportion of managers with a degree was above or below the median in 2006 (or in the first year of observation in case of firms that entered the market later than 2006), using again our two alternative approaches for identifying managers. The results reported in Table A4 and A5 in the Appendix show that the baseline results on the effects of unexpected demand shocks on firm performance generally apply to both subsamples. In particular, there is a strong and highly significant effect of the forecast error on exports for both subsamples, regardless of how the top managers are identified, which suggests that our strategy for identifying unexpected demand shocks is valid also for these more restricted subsamples.

Having established the general validity of our identification strategy, our main objective in this part of the analysis is to re-estimate the results in Table 4 using the above explained sample partition, in order to examine whether and how the within-firm distribution of rents is related to managerial skills. The resulting estimates for the two alternative sample partitions are shown in Table 5 and 6, respectively.

[Table 5 and 6 here]

These results are quite striking. In firms with high-skilled managers, we find a strong and significant effect of a demand shock on the wages of the top earners in the firm, but no significant

effect on the wages of the remaining workforce (with point estimates very close to zero). Thus, for this subset of firms, the rent distribution appears to be even more unequal than what is reported in Table 4 using the full sample of firms. This pattern is highly consistent across the two alternative ways of identifying managers. For the remaining subset of firms, however, the picture is very different. When managers are identified by occupational category (Table 5), we find no significant effects on wages for any group of workers, with all point estimates being close to zero. When managers are identified as the top one percent earners in the firm (Table 6), the corresponding estimates are somewhat larger in magnitude and mostly statistically significant. However, the magnitudes of these wage effects are relatively similar for high earners and low earners, and considerably smaller than the average wage effect for high earners in firms with highskilled managers. These results thus suggest that the distribution of rents created by unexpected demand shocks crucially depends on managerial skills. In firms with low-skilled managers, rents are fairly evenly distributed among the workforce. This stands in stark contrast to firms with high-skilled managers, where rent distribution is highly unequal and strongly benefits workers close to the top end of the earnings distribution.

5.5 Discussion

The main result of our analysis is that firm revenue windfalls, in the form of unexpected demand shocks, are partly transmitted to workers in the form of higher average wages, but in a highly unequal way, with most of the wage increases occurring close to the top of the within-firm wage distribution. A first basic observation is that this result is inconsistent with the notion of perfectly competitive labor markets. If firms are wage takers in a market where wages reflect workers' skills, unexpected firm-specific demand shocks would affect wages only if they lead to changes in the skill composition of the firm's workforce, which we find no evidence of. Instead, our results suggest that wages to some extent reflect rent sharing between firms and their workers.

The evidence of rent sharing in wage determination found in our analysis adds to an already sizeable empirical rent-sharing literature (see Card, Cardoso, Heining, and Kline (2018), for an overview). The exact mechanisms by which rents are shared with workers are potentially numerous, though, and not necessarily mutually exclusive. First, rent sharing could be a result of worker bargaining power, either collectively or individually. Collective bargaining power result from the presence and influence of trade unions in wage determination, while individual bargaining power could result from labor market frictions created by hiring and/or training costs, which create rents that can be captured by incumbent workers (see, e.g., Kline, Petkova, Williams, and Zidar (2019)). Second, rent sharing could also be the result of explicit profit-

sharing arrangements, for example in the form of performance-based pay contracts, which may be used to increase productivity (Lazear, 1986, 2000). Third, wage determination might partly result from firms' incentives to induce the desired amount of effort from its workers, in line with the *fair wage* hypothesis of Akerlof and Yellen (1990). If workers' notion of a fair wage is based on an *internal* reference which reflects the firm's ability to pay, such as revenues per worker, the revenue windfall from an unexpected demand shock would be partly transmitted to workers through an increase in what is considered to be a fair wage.¹⁰ Fourth, rent sharing could be due to firms having some monopsony power in the labor market, for example because of market concentration on the demand side or heterogeneous job preferences on the supply side Manning (2021). If each firm faces an upward sloping labor supply curve, an unexpected product market demand shock will be (partly) transmitted to workers in the form of higher wages via higher labor demand.

We would argue that each of the above suggested mechanisms is plausible in the context of Portuguese labor markets, despite the importance of industry-level collective bargaining in Portugal. Although trade union density is very low, a high share of wage contracts are determined by collective agreements at industry level, which might suggest that there is limited room for wage adjustments in response to firm-specific shocks.¹¹ However, it is worth emphasizing that wage determination in Portugal is characterized by a two-tiered wage setting system where firm-specific arrangements result in a mark-up, often of considerable magnitude, on top of the bargained wage floor.¹² Thus, although the presence of collective bargaining might result in some downward wage rigidity, the two-tiered wage setting system still leaves considerable room for firm-specific adjustments to firm-specific shocks.

In the following we exploit our data to look for indications of the relevance of some of the above mentioned rent sharing mechanisms. We start out by considering whether our results could be explained by individual or collective bargaining power. If rent sharing is caused by hiring or training costs that gives individual bargaining power to longer-tenured workers, we would except that the wage effects of a revenue shock are stronger for such workers than for newly hired workers. This hypothesis is explored in Table 7, where we show the wage effects across these two categories of workers, and where we have classified newly hired workers as

¹⁰For fair wage models based on a firm-internal point of reference, see, e.g., Danthine and Kurman (2006), Bastos, Monteiro, and Straume (2009) and Egger and Kreickemeier (2009)).

¹¹Portugal and Vilares (2013) report a union coverage rate of more than 90 percent despite a union density rate of only 11 percent.

 $^{^{12}}$ See Cardoso and Portugal (2005) and Bastos, Monteiro, and Straume (2009). In the latter study, using data for the period 1991 to 2000, wages are found to be more than 25 percent higher than the bargained wage floor, on average.

workers with less than four years of tenure in the firm.¹³

[Table 7]

The results in Table 7 show that the wage effects tend to be more statistically significant for longer-tenured workers, although the magnitudes of the point estimates are quantitatively quite similar for the two groups of workers. Overall, these results give relatively limited support to the hypothesis that rent sharing is related to worker tenure.

An alternative hypothesis is that rent sharing is caused by collective bargaining power. This hypothesis can be pursued by exploiting some heterogeneity in type of wage agreements that exist in our data. Whereas most of the collective wage agreements in Portugal are made at industry or sectorial level, as previously mentioned, there is also a small prevalence of firm-level wage agreements. If trade unions are able to extract some of the rents related to *firm-specific* revenue shocks, we would expect that the resulting wage effects are stronger for workers whose wage contracts are bargained at firm level, all else equal. We explore this hypothesis in Table 8, where we show the estimated wage effects for workers with firm-specific collective agreements relative to workers whose wage contracts result from collective bargaining at a more centralised level.¹⁴

[Table 8 here]

Interestingly, despite a very low number of observations in the group of firms with firmspecific collective agreements, we see that the effect of a revenue shock on base wages is statistically significant and much larger in magnitude for this category of firms than for firms whose wages are bargained at a more centralised level. This might indicate a presence of collective bargaining power, at least for the small subset of firms that are involved in firm-level collective bargaing.

One of the key results emanating from our analysis is the highly unequal distribution of the rents generated by revenue shocks, and that this unequal distribution is mainly driven by wage effects in firms managed by high-skilled managers (as shown in Tables 5 and 6). This might indicate other mechanisms at play, not related to worker bargaining power. More specifically, these cross-firm differences related to managerial skill might suggest that our results are, at least partly, caused by different types of managers implementing different pay systems in the firm.

¹³A similar definition is used by Kline, Petkova, Williams, and Zidar (2019).

¹⁴In order to avoid problems related to workers who move between firms with different types of wage agreements, the estimation samples used in Table 8 include only workers who remained with the same type of collective wage agreement throughout the observation period.

One plausible hypothesis is that performance-based pay is to a larger extent adopted by highskilled managers, and that such pay systems are more prevalent for managers and other workers close to the top end of the wage distribution, who are more likely to have a direct impact on the firm's performance (Juhn, McCue, Monti, and Pierce, 2018). In order to further explore this hypothesis, we decompose the total wage effects reported in Table 5 and 6, showing the effects on each wage component for different types of workers (top earners versus the remaining workers) across the two categories of firms (managed by high-skilled versus low-skilled managers). These results are displayed in Table 9 (where managers defined according to occupational category) and Table 10 (where managers are defined as the top one percent earners in the firm). We show these results for the intermediate wage distribution threshold (top 15 percent earners versus the rest of the workforce), but the estimates are fairly similar if we use different thresholds.

[Table 9 and 10 here]

The results in Table 9 and 10 show that the unequal sharing of rents within the firm seems to a large extent to be driven by changes in overtime pay and other pay, with the demandshock induced increases in these two wage components mainly accruing to the high earners in the firm. Regarding overtime pay, this pattern is much more pronounced among firms with high-skilled managers if these managers are defined as the top one percent earners in the firm. However, a similar difference across the two firm categories is not present if managers instead are identified by occupational category. In contrast, the most consistent pattern is found for the residual wage component *other pay*. Regardless of how managers are identified, among the firms managed by high-skilled managers, an unexpected demand shock leads to a significant increase in other pay that is larger for the high earners in the firm. A similar pattern is completely absent among firms managed by low-skilled managers. This is an interesting observation with respect to the hypothesis that the importance of managerial skill is, at least partly, related to the use of performance-based pay, which would show up in the *other pay* wage component in our data.

5.6 Robustness

In the following we present several robustness checks to the baseline estimates.

5.6.1 Alternative forecast error weights

In our main analysis we have identified the unexpected demand shocks by creating a weighted forecast error variable where destination-year forecast errors at the firm-year level are weighted by the share of destinations in total sales (in the initial year). By using weights that are based on total sales, we implicitly assume that export-related demand shocks have a larger impact on more export-intensive firms, all else equal. Although this seems like a highly reasonable assumption, our approach might be less appropriate if firms make separate strategic decisions (regarding wage contracts, hiring decisions, investment, etc.) for the export-oriented part of the business. Thus, as a robustness check, we have redone our baseline analysis using alternative forecast error weights, where destination-year forecast errors are weighted by the share of destinations in total exports (again in the initial year). The results from these alternative estimations are presented in Table A6 and A7 in the Appendix.

Although there are some differences compared with the baseline results in Table 2 and 3, these new estimates paint the same overall picture. A positive revenue shock leads to significantly higher sales, exports and employment, and it leads to a significant increase in both monthly and hourly wages. The main difference from the baseline results is the magnitude of these effects, which are generally smaller when using the alternative forecast error weights. These differences in magnitudes are consistent with our original rationale for basing the forecast error weights on total sales. If export-related demand shocks have larger effects on more export-intensive firms, such differences will be downplayed when basing the forecast error weights on total exports instead of total sales, thus reducing the magnitude of the estimated effects of the shocks.

5.6.2 Positive versus negative GDP growth

Our analysis is based on the identification of demand shocks as unexpected deviations from an underlying GDP growth trend. In our main analysis we do not distinguish between positive and negative GDP growth. However, the sign of the underlying growth trend might affect how firms respond to unexpected deviations from it. In particular, there is a potential worry that our results might in part be driven by firms' exceptional adjustment policies during years of large global recessions (such as the 2008 financial crisis). In order to explore this issue, we have reestimated our baseline model on two different subsamples, where the forecast errors are defined as deviations from, respectively, a positive and a negative GDP growth trend. More specifically, we split our sample according to the sign of the average weighted GDP growth rate, for each firm in each 3-year period, and re-estimate (3) on each of the two subsamples. The resulting estimates are displayed in Tables A8 and A9.

Regarding the effect of unexpected positive demand shocks on the firm performance variables, the results in Table A8 show mostly positive point estimates regardless of whether the underlying GPD growth trend is positive or negative, although several of these estimates are not statistically significant. In periods with positive GDP growth, an unexpected positive demand shock leads to a significant increase in exports, employment and total wage costs. In the remaining periods, a positive deviation from a negative GDP growth trend has significantly positive effect on sales, value added and value added per worker. For the remaining variables, the effects are not statistically significant, which could be explained by the lower number of observations in each of the two subsamples.

Regarding the wage effects, based on the matched employer-employee data, the results in Panel A of Table A9 show that unexpected positive deviations from a positive demand trend lead to significantly positive effects on both total wages and base wages. The other wage components have positive point estimates without being statistically significant. On the other hand, the results in Panel B, for periods with negative period averages for GDP growth, show no statistically significant effects of forecast errors on any of the wage components. While this might again be due to a substantial drop in the number of observations, compared with the full sample, it might also reflect the presence of some downward wage rigidity.

5.6.3 Lagged responses

Finally, we explore if and how our baseline results depend on the decision to include a time lag on the independent variables. In our baseline analysis, the period definition of all the independent variables is lagged one year compared to the period definition of the dependent variable, which allows us to capture lagged responses to revenue shocks. However, the length of the adjustment period might differ across different types of variables. For example, while it is reasonable to assume that wage adjustments might take some time, sales and export adjustments might happen much faster. In order to investigate this further, we have re-estimated the effects of revenue shocks on the various firm performance measures using a model without any time lags. The results are reported in Table A10 in the Appendix. For several of the variables, such as sales, exports and employment, the estimated effects with lags (Table 2) and without lags (Table A10) are qualitatively and quantitatively very similar. On the other hand, the wage effect ceases to be statistically significant in a model without time lags. These results are consistent with our conjecture that wage adjustments to a revenue shock are likely to take longer time, on average, than adjustments on other variables.

6 Conclusion

In this paper, we examined the effects of unexpected revenue shocks on firm performance and worker compensation. We proposed a new methodology to identify the unexpected component of demand shocks at the firm-level, exploiting errors in the official forecasts in the GDP growth of export markets. In each destination, the unexpected component of demand shocks was measured as the difference between the GDP growth actually observed and recent forecasts published in the World Economic Outlook of the International Monetary Fund. We then aggregated these shocks at the firm-year level, weighting by the initial share of destinations in firms' total sales. Since firms initially served different destinations to a varying degree, they were differentially exposed to these unexpected demand shocks across markets.

In the empirical analysis, we found that unexpected revenue shocks lead firms to increase sales, employment, investment and average wages. Using employer-employee panel data, we reported evidence that unexpected demand shocks are partly transmitted to workers in the form of higher average wages, but in a highly unequal way, with most of the wage increases occurring close to the top of the within-firm wage distribution. We found little evidence of adjustments in the skill composition of the workforce, as quantified either by the share of workers with a degree or estimated individual effects.

These results suggest that wages to some extent reflect rent sharing between firms and their workers. While rent sharing may reflect several mechanisms, our second set of key results show that the unequal average distribution of rents is mainly driven by wage effects in firms managed by high-skilled managers. A plausible hypothesis is that performance-based pay is to a larger extent adopted by high-skilled managers, and that such pay systems are more prevalent for managers and other workers close to the top end of the wage distribution, who are more likely to have a direct impact on the firm's performance. We found that the unequal sharing of rents within the firm seems to a large extent to be driven by changes in overtime pay and other pay, with the demand-shock induced increases in these two wage components mainly accruing to the high earners in the firm. This is consistent with the hypothesis that the importance of managerial skill is, at least partly, related to the use of performance-based pay, which would show up in the *other pay* wage component in our data.

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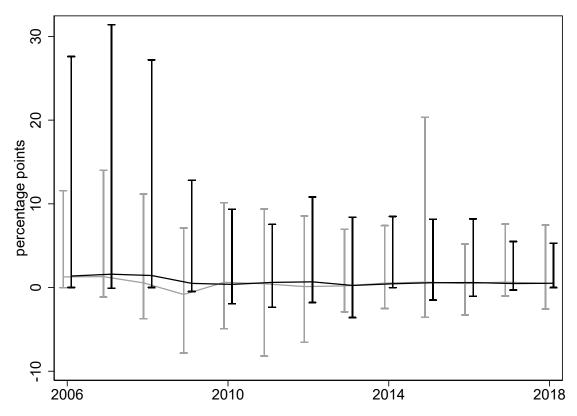


Figure 1: Weighted actual and forecast GDP growth, firm-level data

Notes: Figure depicts means and ranges of weighted actual GDP growth (in gray) and forecast GDP growth (in black) at the firm-level, using the estimation sample. Means are displayed in lines, while ranges are shown in bars.

| Variables | mean | sd | min | max | mean | sd | min | max |
|---|---------|--------|----------|---------|---------|---------------------|----------|---------|
| | | Lev | rels | | | Cha | nges | |
| Weighted forecast error | -0.0576 | 0.7010 | -14.4000 | 5.9410 | 0.1260 | 0.9270 | -4.8760 | 14.4700 |
| Weighted forecast growth | 0.4500 | 1.4550 | -2.8060 | 25.9000 | -0.3420 | 1.7560 | -24.6200 | 8.0250 |
| log sales | 14.8400 | 1.5780 | 7.7600 | 22.7900 | -0.0138 | 0.4420 | -6.4190 | 3.4850 |
| log exports | 12.5000 | 2.6750 | -0.0954 | 22.0300 | -0.0275 | 1.3930 | -14.7800 | 11.7100 |
| $\log (1 + \text{fixed tangible assets})$ | 10.1700 | 3.4660 | 0.0000 | 20.0100 | -0.5010 | 3.0800 | -15.4400 | 15.1200 |
| $\log (1 + \text{intangible assets})$ | 3.2180 | 4.3370 | 0.0000 | 19.4200 | -0.0235 | 4.1620 | -16.9900 | 16.4700 |
| log employment | 3.2400 | 1.3250 | 0.0000 | 10.1200 | -0.0136 | 0.3180 | -4.0430 | 3.1970 |
| log value added | 13.3700 | 1.5330 | 2.5690 | 20.9300 | -0.0730 | 0.5260 | -9.1430 | 4.4620 |
| log value added per worker | 10.1400 | 0.7050 | 0.9600 | 18.2000 | 0.0062 | 0.4580 | -8.9610 | 4.2060 |
| log avg worker pay | 9.6310 | 0.4460 | 6.8120 | 12.9800 | 0.0064 | 0.2030 | -2.4520 | 3.3620 |
| log monthly wage | 7.0310 | 0.4080 | 6.1200 | 10.1300 | 0.0183 | 0.1920 | -2.0650 | 3.1720 |
| log hourly wage | 1.8790 | 0.4110 | 0.9570 | 5.0310 | 0.0161 | 0.1920 | -2.0900 | 3.1690 |
| log monthly base wage | 6.8110 | 0.3740 | 6.1200 | 9.9280 | 0.0139 | 0.1450 | -1.5260 | 2.5270 |
| $\log (1 + \text{overtime pay})$ | 0.7320 | 1.4420 | 0.0000 | 8.1080 | 0.0235 | 1.0080 | -8.1080 | 7.4550 |
| $\log (1 + \text{ other pay})$ | 5.0070 | 1.2980 | 0.0000 | 9.9510 | 0.1200 | 1.1350 | -8.3480 | 8.0050 |
| log total hours | 8.0160 | 1.4070 | 4.9130 | 14.6700 | -0.0049 | 0.4130 | -5.0790 | 5.8480 |
| Share with a degree | 0.1470 | 0.1890 | 0.0000 | 1.0000 | 0.0164 | 0.0943 | -1.0000 | 1.0000 |
| N (obs.) | | 443 | 98 | | | 22 | 199 | |

Table 1: Summary statistics, estimation sample, 2007-2018

Notes: Table reports summary statistics on the firm-level data from the estimation sample for 2007-2018, both in levels and in changes. Levels refer to variables averaged over 3-year periods, changes refer to variation between 3-year periods.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|-----------|-------------|-------------------|-------------------|----------------|-----------|-----------|--------------|
| Dep. variable: | log sales | log exports | $\log (1 + inv.)$ | $\log (1 + inv.)$ | log | log value | log value | log avg. |
| | | | fixed tangible | intangible | employment | added | added per | worker pay |
| | | | assets) | assets) | | | worker | |
| Weighted forecast error | 0.0520*** | 0.1488*** | 0.0998* | 0.1305^{***} | 0.0226^{***} | 0.0394*** | 0.0135 | 0.0090** |
| 5 | (0.0107) | (0.0167) | (0.0527) | (0.0493) | (0.0049) | (0.0095) | (0.0084) | (0.0039) |
| Weighted forecast growth | 0.0404*** | 0.1416*** | 0.0971*** | 0.0807*** | 0.0113*** | 0.0278*** | 0.0150*** | 0.0037^{*} |
| | (0.0055) | (0.0097) | (0.0292) | (0.0293) | (0.0026) | (0.0049) | (0.0045) | (0.0021) |
| Period x region FE | Υ | Y | Y | Y | Υ | Y | Y | Y |
| Period x industry FE | Υ | Υ | Υ | Y | Υ | Y | Υ | Υ |
| N (obs.) | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 |
| N (firms) | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0830 | 0.0320 | 0.0270 | 0.0080 | 0.0460 | 0.0581 | 0.0245 | 0.0250 |
| RSS | 3936 | 41307 | 202918 | 377904 | 2119 | 5726 | 4496 | 885 |

Table 2: Effects of forecast errors and forecast growth on firm performance

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|--------------------------|------------|-----------|--------------|-------------|-----------|------------|-----------|
| Dep. variable: | log | log hourly | log | $\log (1 +$ | $\log (1 +$ | log total | share with | person FE |
| | $\operatorname{monthly}$ | wage | monthly | overtime | other pay) | hours | a degree | |
| | wage | | base wage | pay) | | | | |
| Weighted forecast error | 0.0074^{**} | 0.0073** | 0.0055** | 0.0194^{*} | 0.0212 | 0.0263*** | 0.0001 | -0.0212 |
| 5 | (0.0032) | (0.0032) | (0.0027) | (0.0116) | (0.0168) | (0.0061) | (0.0018) | (0.0154) |
| Weighted forecast growth | 0.0028* | 0.0029* | 0.0009 | 0.0100 | 0,0064 | 0.0113*** | -0.0002 | -0.0048 |
| | (0.0017) | (0.0017) | (0.0013) | (0.0068) | (0.0092) | (0.0032) | (0.0010) | (0.0073) |
| Period x region FE | Y | Y | Y | Y | Y | Υ | Υ | Y |
| Period x industry FE | Υ | Y | Υ | Υ | Y | Υ | Υ | Y |
| N (obs.) | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 12631 |
| N (firms) | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 6012 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0120 | 0.0130 | 0.0340 | 0.0200 | 0.0017 | 0.0340 | 0.0070 | 0.0220 |
| RSS | 799 | 798 | 444 | 21879 | 28275 | 3625 | 194 | 3151 |

Table 3: Effects of forecast errors and forecast growth on worker compensation and worker composition

| | (1) | (2) | (3) | (4) | (5) | (6) | | | | | |
|--|---|--|----------------------------|--|---|--|--|--|--|--|--|
| Dep. variable: | | log monthly wage | | | | | | | | | |
| High vs. low earners | high | low | high | low | high | low | | | | | |
| Definition | 5% | 95% | 15% | 85% | 25% | 85% | | | | | |
| Weighted forecast error | 0.0153^{***} (0.0054) | 0.0052^{**} (0.0026) | 0.0117^{**} (0.0046) | 0.0047^{*} (0.0025) | 0.0087^{**} (0.0043) | 0.0035 (0.0025) | | | | | |
| Weighted forecast growth | (0.0063^{**}) (0.0029) | -0.0004 (0.0014) | (0.0043^{*}) (0.0024) | (0.0012) (0.0012) | (0.0030) (0.0022) | (0.0010) (0.0006) (0.0014) | | | | | |
| Period x region FE | Y | Y | Y | Y | Y | Y | | | | | |
| Period x industry FE | Y | Υ | Υ | Υ | Υ | Υ | | | | | |
| N (obs.) | 20888 | 20888 | 20888 | 20888 | 20888 | 20888 | | | | | |
| N (firms) | 8745 | 8745 | 8745 | 8745 | 8745 | 8745 | | | | | |
| $\begin{array}{c} \text{Adj. } \text{R}^2 \\ \text{RSS} \end{array}$ | $\begin{array}{c} 0.0070\\ 2476\end{array}$ | $\begin{array}{c} 0.0155 \\ 485 \end{array}$ | $0.0086 \\ 1757$ | $\begin{array}{c} 0.0161 \\ 446 \end{array}$ | $\begin{array}{c} 0.0092 \\ 1451 \end{array}$ | $\begin{array}{c} 0.0172 \\ 424 \end{array}$ | | | | | |

Table 4: Effects of forecast errors and forecast growth on worker compensation: high vs low earners

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|----------------|----------|---------------|----------|----------|----------|
| Dep. variable: | | | log mont | hly wage | | |
| High vs. low earners | high | low | high | low | high | low |
| Definition | 5% | 95% | 15% | 85% | 25% | 75% |
| A. Firms with high-skilled manage | ers . | | | | | |
| Weighted forecast error | 0.0363^{***} | -0.0001 | 0.0277^{**} | 0.0029 | 0.0177 | 0.0007 |
| | (0.0134) | (0.0075) | (0.0112) | (0.0067) | (0.0109) | (0.0069) |
| Weighted forecast growth | 0.0195^{***} | -0.0001 | 0.0122** | 0.0013 | 0.0082 | 0.0003 |
| | (0.0071) | (0.0033) | (0.0062) | (0.0031) | (0.0058) | (0.0031) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Y | Y | Y | Y |
| N (obs.) | 5027 | 5027 | 5027 | 5027 | 5027 | 5027 |
| N (firms) | 1991 | 1991 | 1991 | 1991 | 1991 | 1991 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0009 | 0.0256 | 0.0023 | 0.0318 | 0.0054 | 0.0345 |
| RSS | 589.7 | 110.4 | 391.8 | 95.48 | 322.4 | 89.88 |
| B. Firms with low-skilled manage | ers | | | | | |
| Weighted forecast error | 0.0021 | 0.0039 | -0.0011 | 0.0018 | -0.0034 | -0.0005 |
| | (0.0139) | (0.0068) | (0.0115) | (0.0067) | (0.0111) | (0.0069) |
| Weighted forecast growth | 0.0033 | -0.0031 | 0.0016 | -0.0034 | 0.0010 | -0.0034 |
| | (0.0073) | (0.0029) | (0.0060) | (0.0029) | (0.0054) | (0.0029) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Y | Υ | Υ | Υ | Υ | Y |
| N (obs.) | 5207 | 5207 | 5207 | 5207 | 5207 | 5207 |
| N (firms) | 2114 | 2114 | 2114 | 2114 | 2114 | 2114 |
| Adj . R^2 | 0.0114 | 0.0210 | 0.0177 | 0.0196 | 0.0176 | 0.0199 |
| RSS | 623 | 108 | 423 | 98 | 341 | 93 |

Table 5: Effects of forecast errors and forecast growth on worker compensation, high vs low earners, according to managerial skill (defined by occupation)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|---------------|----------|--------------|---------------|----------|--------------|
| Dep. variable: | | | log mont | thly wage | | |
| High versus low earners | high | low | high | low | high | low |
| Definition | 5% | 95% | 15% | 85% | 25% | 85% |
| A. Firms with high-skilled n | nanagers | | | | | |
| Weighted forecast error | 0.0215^{**} | -0.0033 | 0.0152^{*} | -0.0031 | 0.0085 | -0.0048 |
| | (0.0107) | (0.0046) | (0.0092) | (0.0043) | (0.0085) | (0.0042) |
| Weighted forecast growth | 0.0092^{*} | -0.0028 | 0.0054 | -0.0023 | 0.0025 | -0.0033 |
| | (0.0054) | (0.0025) | (0.0045) | (0.0024) | (0.0041) | (0.0025) |
| Period x region FE | Y | Υ | Y | Y | Y | Y |
| Period x industry FE | Y | Y | Y | Y | Y | Υ |
| N (obs.) | 7826 | 7826 | 7826 | 7826 | 7826 | 7826 |
| N (firms) | 3114 | 3114 | 3114 | 3114 | 3114 | 3114 |
| Adj. R^2 | 0.0032 | 0.0192 | 0.0057 | 0.0215 | 0.0079 | 0.0235 |
| RSS | 931 | 178 | 629 | 161 | 516 | 153 |
| B. Firms with low-skilled m | anagers | | | | | |
| Weighted forecast error | 0.0109^{*} | 0.0079** | 0.0090* | 0.0074^{**} | 0.0076 | 0.0065^{*} |
| | (0.0062) | (0.0031) | (0.0054) | (0.0031) | (0.0051) | (0.0031 |
| Weighted forecast growth | 0.0047 | 0.0005 | 0.0036 | 0.0006 | 0.0030 | 0.0004 |
| | (0.0034) | (0.0017) | (0.0030) | (0.0017) | (0.0027) | (0.0017) |
| Period x region FE | Y | Υ | Υ | Y | Υ | Υ |
| Period x industry FE | Υ | Υ | Υ | Y | Υ | Υ |
| N (obs.) | 13058 | 13058 | 13058 | 13058 | 13058 | 13058 |
| N (firms) | 5631 | 5631 | 5631 | 5631 | 5631 | 5631 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0099 | 0.0191 | 0.0118 | 0.0180 | 0.0130 | 0.0185 |
| RSS | 1522 | 301 | 1111 | 279 | 919 | 267 |

Table 6: Effects of forecast errors and forecast growth on worker compensation, high vs low earners, according to managerial skill (defined as top 1% earners)

| | (1) | (2) | (3) | (4) |
|--|-------------------|---------------|---------------|--------------------|
| Dep. variable: | log monthly | log monthly | $\log (1 +$ | $\log (1 + other)$ |
| | wage | base wage | overtime pay) | pay) |
| A. Newly hired workers (less | than 4 years) | | | |
| Weighted forecast error | 0.0081^{*} | 0.0062 | 0.0107 | 0.0268 |
| | (0.0048) | (0.0046) | (0.0152) | (0.0215) |
| Weighted forecast growth | 0.0041 | 0.0031 | 0.0062 | 0.0058 |
| | (0.0026) | (0.0025) | (0.0090) | (0.0115) |
| Period x region FE | Υ | Υ | Y | Υ |
| Period x industry FE | Υ | Y | Υ | Υ |
| N (obs.) | 18700 | 18700 | 18700 | 18700 |
| N (firms) | 8149 | 8149 | 8149 | 8149 |
| Adj. \mathbb{R}^2 | 0.0079 | 0.0153 | 0.0229 | 0.0023 |
| RSS | 1402 | 1196 | 23123 | 28551 |
| B. Longer-tenured workers (| at least 4 years) | | | |
| Weighted forecast error | 0.0082^{**} | 0.0065^{**} | 0.0264^{**} | 0.0145 |
| | (0.0038) | (0.0031) | (0.0132) | (0.0195) |
| Weighted forecast growth | 0.0028 | 0.0005 | 0.0134^{*} | 0.0058 |
| | (0.0020) | (0.0015) | (0.0076) | (0.0101) |
| Period x region FE | Υ | Y | Υ | Υ |
| Period x industry FE | Y | Υ | Υ | Y |
| N (obs.) | 21418 | 21418 | 21418 | 21418 |
| N (firms) | 9019 | 9019 | 9019 | 9019 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0220 | 0.0395 | 0.0190 | 0.0015 |
| RSS | 980 | 554 | 21801 | 29238 |

Table 7: Effects of forecast errors and forecast growth on worker compensation: longer-tenured vs newly hired workers

| | (1) | (2) | (3) | (4) |
|--|---------------|---------------|---------------|--------------------|
| Dep. variable: | log monthly | log monthly | $\log (1 +$ | $\log (1 + other)$ |
| | wage | base wage | overtime pay) | pay) |
| A. Firm-level wage agreement | | | | |
| Weighted forecast error | 0.0245 | 0.0977^{**} | -0.1292 | -0.0889 |
| | (0.0915) | (0.0373) | (0.3344) | (0.2497) |
| Weighted forecast growth | 0.0528 | 0.0490^{**} | -0.0557 | 0.0551 |
| | (0.0640) | (0.0236) | (0.3453) | (0.1568) |
| Period x region FE | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Y | Y |
| N (obs.) | 90 | 90 | 90 | 90 |
| N (firms) | 39 | 39 | 39 | 39 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.4030 | 0.3890 | 0.3850 | 0.5130 |
| RSS | 0.4860 | 0.1960 | 18.8300 | 5.5760 |
| B. More centralised wage agreen | nents | | | |
| Weighted forecast error | 0.0071^{**} | 0.0056^{**} | 0.0197^{*} | 0.0200 |
| | (0.0032) | (0.0027) | (0.0116) | (0.0169) |
| Weighted forecast growth | 0.0026 | 0.0010 | 0.0102 | 0.0056 |
| | (0.0017) | (0.0013) | (0.0068) | (0.0092) |
| Period x region FE | Y | Y | Y | Y |
| Period x industry FE | Y | Υ | Υ | Υ |
| N (obs.) | 22051 | 22051 | 22051 | 22051 |
| N (firms) | 9254 | 9254 | 9254 | 9254 |
| Adj. \mathbb{R}^2 | 0.0124 | 0.0346 | 0.0189 | 0.0019 |
| RSS | 792 | 438 | 21669 | 28234 |

Table 8: Effects of forecast errors and forecast growth on worker compensation: firm-level vs more centralised wage agreements

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|----------|----------|--------------|----------|--------------|--------------|
| Dep. variable: | log bas | se wage | log over | time pay | log otl | ner pay |
| High versus low earners | high | low | high | low | high | low |
| Definition | 15% | 85% | 15% | 85% | 15% | 85% |
| A. Firms with high-skilled | managers | | | | | |
| Weighted forecast error | 0.0115 | 0.0012 | 0.0719^{*} | -0.0017 | 0.1071^{*} | 0.0736^{*} |
| | (0.0091) | (0.0054) | (0.0433) | (0.0360) | (0.0596) | (0.0421) |
| Weighted forecast growth | 0.0009 | -0.0016 | 0.0264 | -0.0069 | 0.0420 | 0.0324^{*} |
| | (0.0042) | (0.0024) | (0.0248) | (0.0216) | (0.0318) | (0.0189) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Υ | Υ | Υ | Y |
| N (obs.) | 5027 | 5027 | 5027 | 5027 | 5027 | 5027 |
| N (firms) | 1991 | 1991 | 1991 | 1991 | 1991 | 1991 |
| $Adj. R^2$ | 0.0188 | 0.0634 | 0.0401 | 0.0462 | 0.0034 | 0.0062 |
| RSS | 211 | 53 | 7889 | 5799 | 8118 | 3797 |
| B. Firms with low-skilled n | nanagers | | | | | |
| Weighted forecast error | 0.0022 | 0.0050 | 0.0597^{*} | 0.0171 | 0.0179 | 0.0265 |
| | (0.0088) | (0.0053) | (0.0359) | (0.0321) | (0.0532) | (0.0417) |
| Weighted forecast growth | -0.0001 | 0.0003 | 0.0238 | 0.0070 | 0.0004 | -0.0339* |
| | (0.0050) | (0.0023) | (0.0198) | (0.0178) | (0.0299) | (0.0199) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Υ | Υ | Υ | Υ |
| N (obs.) | 5207 | 5207 | 5207 | 5207 | 5207 | 5207 |
| N (firms) | 2114 | 2114 | 2114 | 2114 | 2114 | 2114 |
| $Adj. R^2$ | 0.0181 | 0.0544 | 0.0331 | 0.0237 | 0.0132 | -0.0003 |
| RSS | 305 | 55 | 6655 | 5234 | 9702 | 4994 |

Table 9: Effects of forecast errors and forecast growth on different wage components, high vs low earners, according to managerial skill (defined by occupation)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|----------|----------------|---------------|----------|--------------|----------|
| Dep. variable: | log ba | se wage | log over | time pay | log oth | ner pay |
| High versus low earners | high | low | high | low | high | low |
| Definition | 15% | 85% | 15% | 85% | 15% | 85% |
| A. Firms with high-skilled | nanagers | | | | | |
| Weighted forecast error | 0.0087 | -0.0018 | 0.0717^{**} | 0.0160 | 0.0703^{*} | 0.0269 |
| | (0.0074) | (0.0036) | (0.0321) | (0.0272) | (0.0412) | (0.0284) |
| Weighted forecast growth | 0.0012 | -0.0029 | 0.0280 | 0.0083 | -0.0059 | -0.0045 |
| | (0.0033) | (0.0020) | (0.0178) | (0.0151) | (0.0249) | (0.0142) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Υ | Y | Υ | Y |
| N (obs.) | 7826 | 7826 | 7826 | 7826 | 7826 | 7826 |
| N (firms) | 3114 | 3114 | 3114 | 3114 | 3114 | 3114 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0137 | 0.0454 | 0.0213 | 0.0298 | 0.0091 | 0.0088 |
| RSS | 389 | 92 | 12938 | 9347 | 14076 | 6957 |
| B. Firms with low-skilled n | anagers | | | | | |
| Weighted forecast error | 0.0072 | 0.0069^{***} | 0.0181 | 0.0170 | 0.0087 | 0.0231 |
| | (0.0046) | (0.0024) | (0.0168) | (0.0163) | (0.0281) | (0.0232) |
| Weighted forecast growth | 0.0024 | 0.0010 | 0.0154 | 0.0061 | 0.0091 | 0.0090 |
| | (0.0025) | (0.0013) | (0.0100) | (0.0095) | (0.0155) | (0.0120) |
| Period x region FE | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Y | Υ | Υ | Υ | Y |
| N (obs.) | 13058 | 13058 | 13058 | 13058 | 13058 | 13058 |
| N (firms) | 5631 | 5631 | 5631 | 5631 | 5631 | 5631 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0211 | 0.058 | 0.0174 | 0.0171 | 0.0045 | 0.0018 |
| RSS | 765 | 156 | 14868 | 11253 | 27679 | 16695 |

Table 10: Effects of forecast errors and forecast growth on different wage components, high vs low earners, according to managerial skill (defined as top 1% earners)

A.1 Appendix Tables

| Period | | 1 [200 | 7-2009] | | | 2 [2010 | 0-2012] | | Change = | = Period | 2-Period 1 | |
|---|---------|--------|----------|---------|---------|---------|---------|---------|----------|---------------------|------------|---------|
| Variables | mean | sd | min | \max | mean | sd | min | \max | mean | sd | min | \max |
| Weighted forecast error | -0.3020 | 1.4650 | -14.4000 | 2.0080 | 0.0091 | 0.2960 | -4.0890 | 3.7550 | 0.3120 | 1.4220 | -4.8760 | 14.4700 |
| Weighted forecast growth | 1.3210 | 2.7770 | -0.0472 | 25.9000 | 0.0802 | 0.5990 | -2.4560 | 6.6090 | -1.2410 | 2.4300 | -24.6200 | 1.2220 |
| log sales | 14.7600 | 1.5290 | 9.5800 | 22.5800 | 14.6700 | 1.5990 | 7.7600 | 22.7100 | -0.0855 | 0.4570 | -6.4190 | 3.0240 |
| log exports | 12.2400 | 2.6250 | 1.4820 | 21.1100 | 12.2500 | 2.6930 | -0.0954 | 21.6800 | 0.0079 | 1.5010 | -11.1900 | 11.7100 |
| $\log (1 + \text{fixed tangible assets})$ | 10.6700 | 2.9090 | 0.0000 | 19.5900 | 9.7280 | 3.6330 | 0.0000 | 20.0100 | -0.9450 | 3.0800 | -15.4400 | 14.1300 |
| $\log (1 + \text{intangible assets})$ | 3.0630 | 4.3820 | 0.0000 | 19.2000 | 2.9920 | 4.1930 | 0.0000 | 19.3600 | -0.0709 | 4.5440 | -16.9900 | 14.6000 |
| log employment | 3.1970 | 1.3110 | 0.0000 | 9.8830 | 3.1540 | 1.3190 | 0.0000 | 9.8710 | -0.0428 | 0.3240 | -3.6020 | 3.1970 |
| log value added | 13.2900 | 1.4850 | 7.2170 | 20.6800 | 13.2000 | 1.5480 | 4.9890 | 20.7100 | -0.0926 | 0.5200 | -5.7110 | 4.1800 |
| log value added per worker | 10.1000 | 0.6900 | 5.4250 | 18.2000 | 10.0500 | 0.7340 | 3.8900 | 17.6300 | -0.0500 | 0.4660 | -4.5160 | 3.9600 |
| log avg worker pay | 9.6130 | 0.4640 | 7.2320 | 12.5900 | 9.6250 | 0.4550 | 6.8120 | 12.9800 | 0.0114 | 0.2190 | -2.3320 | 2.6010 |
| log monthly wage | 7.0070 | 0.4310 | 6.1200 | 9.3610 | 7.0120 | 0.4090 | 6.2110 | 10.0300 | 0.0041 | 0.2190 | -2.0650 | 2.2160 |
| log hourly wage | 1.8590 | 0.4340 | 0.9570 | 4.2860 | 1.8590 | 0.4130 | 1.0580 | 4.9270 | -0.0002 | 0.2190 | -2.0900 | 2.2160 |
| log monthly base wage | 6.7910 | 0.3930 | 6.1200 | 8.7350 | 6.8080 | 0.3790 | 6.1890 | 9.9280 | 0.0167 | 0.1660 | -1.4970 | 2.5270 |
| $\log (1 + \text{overtime pay})$ | 0.7040 | 1.4570 | 0.0000 | 6.9490 | 0.6460 | 1.3770 | 0.0000 | 7.4550 | -0.0581 | 1.0650 | -6.0660 | 7.4550 |
| $\log (1 + \text{ other pay})$ | 4.7670 | 1.6530 | 0.0000 | 9.2720 | 4.9070 | 1.2970 | 0.0000 | 9.0240 | 0.1400 | 1.4410 | -8.3480 | 8.0050 |
| log total hours | 7.9270 | 1.3880 | 4.9130 | 14.4500 | 7.9410 | 1.4050 | 4.9900 | 14.3900 | 0.0134 | 0.4670 | -5.0790 | 5.8480 |
| share with a degree | 0.1230 | 0.1790 | 0.0000 | 1.0000 | 0.1380 | 0.1870 | 0.0000 | 1.0000 | 0.0149 | 0.1010 | -1.0000 | 1.0000 |
| N (obs.) | | 8 | 540 | | | 85 | 40 | | | 8 | 540 | |

Table A1: Summary statistics, estimation sample, by 3-year period

Notes: Table reports summary statistics on the firm-level data from the estimation sample for 2007-2009 and 2010-2012, both in levels and in changes. Levels refer to variables averaged over 3-year periods, changes refer to variation between 3-year periods.

| Period | | 2 [2010 | 0-2012] | | | 3 [2013 | 8-2015] | | Change = | = Period | 3-Period 2 | |
|---|---------|---------------------|---------|---------|---------|---------------------|---------|---------|----------|---------------------|------------|---------|
| Variables | mean | sd | min | max | mean | sd | \min | max | mean | sd | min | \max |
| Weighted forecast error | 0.0122 | 0.2880 | -4.0890 | 2.9260 | -0.0342 | 0.1990 | -2.9710 | 1.8380 | -0.0464 | 0.2710 | -4.8010 | 3.6580 |
| Weighted forecast growth | 0.0856 | 0.5980 | -2.4560 | 6.6090 | 0.2950 | 0.8830 | -2.5010 | 7.8300 | 0.2090 | 0.5020 | -1.7510 | 8.0250 |
| log sales | 14.8500 | 1.5450 | 10.0100 | 22.7100 | 14.8300 | 1.6000 | 9.3500 | 22.7900 | -0.0140 | 0.4320 | -4.2830 | 3.3480 |
| log exports | 12.5500 | 2.6210 | -0.0954 | 21.6800 | 12.6100 | 2.6650 | 2.2330 | 22.0300 | 0.0677 | 1.3110 | -11.8600 | 11.6600 |
| $\log (1 + \text{fixed tangible assets})$ | 10.2200 | 3.2060 | 0.0000 | 20.0100 | 9.8400 | 3.7510 | 0.0000 | 19.4400 | -0.3790 | 3.0750 | -14.8500 | 14.0800 |
| $\log (1 + \text{intangible assets})$ | 3.2670 | 4.2940 | 0.0000 | 19.3600 | 3.1830 | 4.2890 | 0.0000 | 19.4200 | -0.0843 | 3.8950 | -16.6600 | 15.6600 |
| log employment | 3.2560 | 1.3060 | 0.0000 | 9.8710 | 3.2220 | 1.3360 | 0.0000 | 9.9950 | -0.0341 | 0.3280 | -4.0430 | 2.2580 |
| log value added | 13.3700 | 1.4820 | 8.7560 | 20.7100 | 13.3500 | 1.5830 | 2.5690 | 20.7700 | -0.0228 | 0.5550 | -9.1430 | 4.4620 |
| log value added per worker | 10.1200 | 0.6660 | 6.4220 | 17.6300 | 10.1400 | 0.7440 | 0.9600 | 17.1000 | 0.0109 | 0.4770 | -8.9610 | 4.2060 |
| log avg worker pay | 9.6470 | 0.4400 | 7.3630 | 12.9800 | 9.6210 | 0.4440 | 7.3900 | 12.7000 | -0.0263 | 0.1950 | -1.7050 | 3.3620 |
| log monthly wage | 7.0250 | 0.4010 | 6.2190 | 10.0300 | 7.0380 | 0.4070 | 6.2160 | 10.0800 | 0.0133 | 0.1720 | -1.4040 | 1.6640 |
| log hourly wage | 1.8720 | 0.4040 | 1.0650 | 4.9270 | 1.8850 | 0.4100 | 1.0620 | 4.9500 | 0.0130 | 0.1720 | -1.4040 | 1.6600 |
| log monthly base wage | 6.8180 | 0.3750 | 6.2190 | 9.9280 | 6.8050 | 0.3730 | 6.2160 | 9.3350 | -0.0131 | 0.1270 | -1.1400 | 1.8780 |
| $\log (1 + \text{overtime pay})$ | 0.7030 | 1.4200 | 0.0000 | 7.4550 | 0.6960 | 1.3820 | 0.0000 | 8.1080 | -0.0074 | 0.9650 | -5.9080 | 5.3940 |
| $\log (1 + \text{ other pay})$ | 4.9740 | 1.1960 | 0.0000 | 8.5260 | 5.1390 | 1.1600 | 0.0000 | 9.8650 | 0.1650 | 0.9510 | -6.1760 | 6.5540 |
| log total hours | 8.0550 | 1.3870 | 5.0240 | 14.3900 | 8.0080 | 1.4240 | 5.0240 | 14.5300 | -0.0475 | 0.4010 | -4.8830 | 2.9790 |
| share with a degree | 0.1420 | 0.1860 | 0.0000 | 1.0000 | 0.1590 | 0.1960 | 0.0000 | 1.0000 | 0.0167 | 0.0914 | -1.0000 | 1.0000 |
| N (obs.) | | 71 | 92 | | | 71 | 92 | | | 7 | 192 | |

Table A1: Summary statistics, estimation sample, by 3-year period (cont.)

Notes: Table reports summary statistics on the firm-level data from the estimation sample for 2010-2012 and 2013-2015, both in levels and in changes. Levels refer to variables averaged over 3-year periods, changes refer to variation between 3-year periods.

| Period | 3 [2013-2015] | | | | 4 [2016-2018] | | | | $Change = Period \ 4-Period \ 3$ | | | |
|---|---------------|---------------------|---------|---------|---------------|---------------------|---------|---------|----------------------------------|--------|----------|---------|
| Variables | mean | sd | \min | max | mean | sd | \min | max | mean | sd | \min | max |
| Weighted forecast error | -0.0278 | 0.1930 | -2.9710 | 1.8380 | 0.0438 | 0.3900 | -4.3230 | 5.9410 | 0.0716 | 0.3410 | -3.5240 | 5.2380 |
| Weighted forecast growth | 0.2930 | 0.8560 | -2.5010 | 7.8300 | 0.5240 | 0.7050 | -2.8060 | 5.3000 | 0.2310 | 0.8780 | -5.8550 | 3.6170 |
| log sales | 14.9600 | 1.5520 | 10.5100 | 22.7900 | 15.0400 | 1.6210 | 9.4850 | 22.6300 | 0.0811 | 0.4130 | -5.4650 | 3.4850 |
| log exports | 12.8500 | 2.5660 | 2.2260 | 22.0300 | 12.6600 | 2.8330 | -0.0180 | 21.8600 | -0.1800 | 1.3190 | -14.7800 | 10.8700 |
| $\log (1 + \text{fixed tangible assets})$ | 3.30200 | 1.3210 | 0.0000 | 9.9950 | 3.3500 | 1.3530 | 0.0000 | 10.1200 | -0.0515 | 3.0070 | -13.3400 | 15.1200 |
| $\log (1 + \text{intangible assets})$ | 10.3200 | 3.3110 | 0.0000 | 19.4400 | 10.270 | 3.8890 | 0.0000 | 19.6600 | 0.1070 | 3.9120 | -15.6600 | 16.4700 |
| log employment | 3.4100 | 4.3440 | 0.0000 | 17.9100 | 3.5160 | 4.5290 | 0.0000 | 18.5900 | 0.0478 | 0.2890 | -3.3040 | 2.7730 |
| log value added | 13.4900 | 1.5000 | 7.8800 | 20.7700 | 13.6200 | 1.5700 | 7.0810 | 20.9300 | 0.1230 | 0.4730 | -4.9180 | 3.2530 |
| log value added per worker | 10.2000 | 0.6630 | 6.2700 | 17.1000 | 10.2700 | 0.6990 | 5.0820 | 18.1100 | 0.0751 | 0.4140 | -4.6490 | 3.2410 |
| log avg worker pay | 9.6260 | 0.4320 | 6.9720 | 11.9200 | 9.6630 | 0.4270 | 7.2660 | 12.0800 | 0.0362 | 0.1850 | -2.4520 | 2.3920 |
| log monthly wage | 7.0390 | 0.3990 | 6.2160 | 10.0800 | 7.0820 | 0.3880 | 6.2960 | 10.1300 | 0.0425 | 0.1700 | -1.5260 | 3.1720 |
| log hourly wage | 1.8850 | 0.4020 | 1.0620 | 4.9500 | 1.9260 | 0.3910 | 1.1430 | 5.0310 | 0.0409 | 0.1700 | -1.5260 | 3.1690 |
| log monthly base wage | 6.8040 | 0.3640 | 6.1940 | 9.3350 | 6.8450 | 0.3520 | 6.2960 | 9.0150 | 0.0404 | 0.1260 | -1.5260 | 1.1890 |
| $\log (1 + \text{overtime pay})$ | 0.7600 | 1.4300 | 0.0000 | 8.1080 | 0.9260 | 1.5840 | 0.0000 | 6.7380 | 0.1660 | 0.9600 | -8.1080 | 5.9510 |
| $\log (1 + \text{ other pay})$ | 5.1570 | 1.1360 | 0.0000 | 9.8650 | 5.2000 | 1.0920 | 0.0000 | 9.9510 | 0.0431 | 0.8160 | -6.7460 | 6.7280 |
| log total hours | 8.0980 | 1.4010 | 5.0240 | 14.5300 | 8.1170 | 1.4280 | 5.0240 | 14.6700 | 0.0182 | 0.3420 | -3.4450 | 2.6390 |
| share with a degree | 0.1580 | 0.1890 | 0.0000 | 1.0000 | 0.1760 | 0.1980 | 0.0000 | 1.0000 | 0.0181 | 0.0888 | -1.0000 | 1.0000 |
| N (obs.) | 6467 | | | | 6467 | | | | 6467 | | | |

Table A1: Summary statistics, estimation sample, by 3-year period (cont.)

Notes: Table reports summary statistics on the firm-level data from the estimation sample for 2013-2015 and 2016-2018, both in levels and in changes. Levels refer to variables averaged over 3-year periods, changes refer to variation between 3-year periods.

| | | Export share | | | |
|--------------------|-----------------------|--------------|------------|--|--|
| | Export | | Estimation | | |
| | rank | All exports | sample | | |
| Spain | 1 | 0.2818 | 0.2741 | | |
| Germany | 2 | 0.1307 | 0.1384 | | |
| France | 3 | 0.1307 | 0.1322 | | |
| United Kingdom | 4 | 0.0676 | 0.0650 | | |
| United States | 5 | 0.0633 | 0.0681 | | |
| Netherlands | 6 | 0.0356 | 0.0344 | | |
| Angola | 7 | 0.0356 | 0.0315 | | |
| Italy | 8 | 0.0346 | 0.0350 | | |
| Belgium | 9 | 0.0303 | 0.0303 | | |
| Singapore | 10 | 0.0215 | 0.0243 | | |
| Sweden | 11 | 0.0114 | 0.0117 | | |
| Switzerland | 12 | 0.0079 | 0.0075 | | |
| Brazil | 13 | 0.0075 | 0.0076 | | |
| Finland | 14 | 0.0074 | 0.0078 | | |
| Denmark | 15 | 0.0069 | 0.0067 | | |
| China | 16 | 0.0063 | 0.0070 | | |
| Poland | 17 | 0.0060 | 0.0064 | | |
| Turkey | 18 | 0.0056 | 0.0060 | | |
| Cape Verde | 19 | 0.0054 | 0.0050 | | |
| Austria | 20 | 0.0054 | 0.0054 | | |
| Ireland | 21 | 0.0051 | 0.0050 | | |
| Morocco | 22 | 0.0048 | 0.0046 | | |
| Canada | 23 | 0.0046 | 0.0046 | | |
| Mexico | 24 | 0.0040 | 0.0042 | | |
| Czech Republic | 25 | 0.0037 | 0.0038 | | |
| Greece | 26 | 0.0036 | 0.0035 | | |
| Hungary | 27 | 0.0034 | 0.0036 | | |
| Norway | 28 | 0.0033 | 0.0030 | | |
| Japan | 29 | 0.0032 | 0.0034 | | |
| Russian Federation | 30 | 0.0029 | 0.0029 | | |
| Malaysia | 31 | 0.0026 | 0.0029 | | |
| Hong Kong | 32 | 0.0024 | 0.0024 | | |
| South Africa | 33 | 0.0022 | 0.0023 | | |
| Romania | 34 | 0.0022 | 0.0022 | | |
| Israel | 35 | 0.0021 | 0.0021 | | |
| Mozambique | 36 | 0.0021 | 0.0020 | | |
| Australia | 37 | 0.0020 | 0.0021 | | |
| Algeria | 38 | 0.0019 | 0.0019 | | |
| Chile | 39 | 0.0016 | 0.0018 | | |
| Tunisia | 40 | 0.0016 | 0.0016 | | |

Table A2: Main export markets, ranked according to export shares in 2006

Notes: Table reports the share of exports to each of the top 40 destinations in 2006, both in the full customs data and in the estimation sample.

| | Firms w | ith Z-score | below the | median | Firms wi | Firms with Z-score above the median | | | |
|---|---------|---------------------|-----------|----------|----------|-------------------------------------|---------|---------|--|
| | mean | sd | \min | max | mean | sd | min | \max | |
| log sales | 16.6200 | 1.4080 | 12.6600 | 21.5200 | 17.3600 | 1.4470 | 13.5600 | 22.4700 | |
| Foreign capital | 0.2050 | 0.4040 | 0.0000 | 1.0000 | 0.3320 | 0.4710 | 0.0000 | 1.0000 | |
| Public capital | 0.0423 | 0.2010 | 0.0000 | 1.0000 | 0.0174 | 0.1310 | 0.0000 | 1.0000 | |
| Export status | 0.6980 | 0.4600 | 0.0000 | 1.0000 | 0.7080 | 0.4550 | 0.0000 | 1.0000 | |
| Exports to sales ratio | 0.2940 | 0.3690 | 0.0000 | 1.0000 | 0.2910 | 0.3650 | 0.0000 | 1.0000 | |
| % of female employees | 0.3700 | 0.2690 | 0.0000 | 0.9960 | 0.3930 | 0.2360 | 0.0000 | 0.9860 | |
| Firm age | 25.5900 | 27.2800 | 0.0000 | 516.0000 | 26.7100 | 20.0000 | 0.0000 | 126 | |
| % of employees with a degree | 0.1290 | 0.1600 | 0.0000 | 1.0000 | 0.1990 | 0.2020 | 0.0000 | 0.9100 | |
| Mean employee ability | 0.1070 | 0.2530 | -0.6400 | 1.2520 | 0.2080 | 0.2780 | -0.4710 | 1.5570 | |
| Managers defined as top 1% earners | | | | | | | | | |
| - Mean managerial ability | 1.1070 | 0.5290 | -0.2150 | 5.3800 | 1.3430 | 0.4900 | -0.1340 | 4.8130 | |
| - $\%$ of managers with a degree | 0.5250 | 0.3760 | 0.0000 | 1.0000 | 0.6240 | 0.3360 | 0.0000 | 1.0000 | |
| log employment | 5.1190 | 1.0650 | 1.0990 | 9.1120 | 5.4650 | 1.0920 | 1.9460 | 10.0600 | |
| $\%$ of employees for which FE were computed 3 | 0.4630 | 0.2400 | 0.0004 | 1.0000 | 0.5320 | 0.2220 | 0.0002 | 1.0000 | |
| Standardized management Z-score | -0.7920 | 0.5760 | -3.3850 | -0.0539 | 0.7910 | 0.6450 | -0.0526 | 3.0360 | |
| N (firms) | | 80 | 4 | | | 80 | 5 | | |
| Managers defined by occupation | | | | | | | | | |
| - Mean managerial ability | 1.0140 | 0.4660 | -0.5190 | 2.8980 | 1.1380 | 0.4060 | -0.5850 | 2.7700 | |
| - $\%$ of managers with a degree | 0.6040 | 0.3510 | 0.0000 | 1.0000 | 0.6520 | 0.3110 | 0.0000 | 1.0000 | |
| N (firms) | | 66 | 8 | | | 73 | 6 | | |

Table A3: Summary statistics, firms in the management survey data, 2016

Notes: Employee ability is the mean level of individual fixed effect measured over the period 2010-2015. Managerial ability is the mean employee ability for managers in 2010-2015.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|---------------|----------------|-------------------|-------------------|----------------|----------------|--------------|------------|
| Dep. variable: | log sales | log exports | $\log (1 + inv.)$ | $\log (1 + inv.)$ | \log | log value | log value | log avg. |
| | | | fixed tangible | intangible | employment | added | added per | worker pay |
| | | | assets) | assets) | | | worker | |
| A. Firms with high-skill managers | | | | | | | | |
| Weighted forecast error | 0.0447^{**} | 0.1868^{***} | 0.0053 | 0.1471 | 0.0289^{**} | 0.0586^{**} | 0.0245 | 0.0066 |
| | (0.0186) | (0.0488) | (0.1009) | (0.1736) | (0.0132) | (0.0235) | (0.0194) | (0.0058) |
| Weighted forecast growth | 0.0238^{**} | 0.1631^{***} | 0.1364^{***} | 0.0393 | 0.0169^{***} | 0.0368^{***} | 0.0178^{*} | 0.0002 |
| | (0.0093) | (0.0268) | (0.0523) | (0.0973) | (0.0061) | (0.0125) | (0.0104) | (0.0028) |
| Period x region FE | Y | Υ | Y | Y | Υ | Y | Y | Υ |
| Period x industry FE | Y | Υ | Υ | Υ | Υ | Υ | Y | Y |
| N (obs.) | 5027 | 5027 | 5027 | 5027 | 5027 | 5027 | 5027 | 5027 |
| N (firms) | 1991 | 1991 | 1991 | 1991 | 1991 | 1991 | 1991 | 1991 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.1410 | 0.0388 | 0.0452 | 0.0174 | 0.0987 | 0.0665 | 0.0249 | 0.0250 |
| RSS | 704 | 9629 | 28428 | 105229 | 398 | 1146 | 842 | 124 |
| B. Firms with low-skill managers | | | | | | | | |
| Weighted forecast error | 0.0201 | 0.1080*** | 0.1075 | 0.2645^{**} | 0.0172 | 0.0086 | -0.0136 | 0.0010 |
| | (0.0203) | (0.0366) | (0.1233) | (0.1237) | (0.0105) | (0.0213) | (0.0187) | (0.0091) |
| Weighted forecast growth | 0.0186** | 0.1314*** | 0.0115 | 0.1773^{***} | 0.0052 | 0.0049 | -0.0012 | 0.0021 |
| | (0.0090) | (0.0203) | (0.0626) | (0.0687) | (0.0055) | (0.0096) | (0.0079) | (0.0039) |
| Period x region FE | Y | Υ | Υ | Υ | Υ | Y | Y | Υ |
| Period x industry FE | Υ | Y | Υ | Υ | Y | Υ | Y | Υ |
| N (obs.) | 5207 | 5207 | 5207 | 5207 | 5207 | 5207 | 5207 | 5207 |
| N (firms) | 2114 | 2114 | 2114 | 2114 | 2114 | 2114 | 2114 | 2114 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0812 | 0.0384 | 0.0303 | 0.0107 | 0.0595 | 0.0742 | 0.0300 | 0.0442 |
| RSS | 780 | 8083 | 37456 | 91862 | 349 | 1008 | 756 | 138 |

Table A4: Effects of forecast errors and forecast growth on firm performance, according to managerial skill (defined by occupation)

Notes: In each column, the dependent variable is the change between the averages of each 3-year period. Standard errors are clustered at firm-level. *10% level of significance, **5% level of significance, **5% level of significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|----------------|----------------|---------------------------|---|----------------|----------------|---------------------|------------|
| Dep. variable: | log sales | log exports | $\log (1 + inv.)$ | $\log (1 + inv.)$ | log | log value | log value | log avg. |
| | | | fixed tangible assets) | $\begin{array}{c} { m intangible} \\ { m assets} \end{array}$ | employment | added | added per worker | worker pay |
| A. Firms with high-skill ma | anagers | | | | | | | |
| Weighted forecast error | 0.0248* | 0.1332^{***} | 0.0436 | 0.1419 | 0.0185^{**} | 0.0366^{**} | 0.0140 | 0.0012 |
| | (0.0134) | (0.0293) | (0.0814) | (0.1156) | (0.0083) | (0.0145) | (0.0131) | (0.0080) |
| Weighted forecast growth | 0.0211^{***} | 0.1417^{***} | 0.1200^{**} | 0.1068 | 0.0101^{**} | 0.0269^{***} | 0.0153^{**} | -0.0000 |
| | (0.0071) | (0.0174) | (0.0476) | (0.0668) | (0.0043) | (0.0081) | (0.0072) | (0.0039) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Υ | Y |
| Period x industry FE | Υ | Y | Y | Y | Υ | Υ | Υ | Y |
| N (obs.) | 7826 | 7826 | 7826 | 7826 | 7826 | 7826 | 7826 | 7826 |
| N (firms) | 3114 | 3114 | 3114 | 3114 | 3114 | 3114 | 3114 | 3114 |
| $Adj. R^2$ | 0.115 | 0.0285 | 0.0393 | 0.0155 | 0.0692 | 0.0706 | 0.0343 | 0.0145 |
| RSS | 1225 | 15811 | 50550 | 155896 | 684 | 1836 | 1402 | 260 |
| B. Firms with low-skill ma | nagers | | | | | | | |
| Weighted forecast error | 0.0502*** | 0.1435^{***} | 0.1092 | 0.1227^{*} | 0.0228^{***} | 0.0348^{***} | 0.0097 | 0.0027 |
| | (0.0156) | (0.0239) | (0.0676) | (0.0653) | (0.0064) | (0.0127) | (0.0114) | (0.0045) |
| Weighted forecast growth | 0.0352^{***} | 0.1395^{***} | 0.0701^{*} | 0.0769^{**} | 0.0106^{***} | 0.0197^{***} | 0.0075 | 0.0022 |
| | (0.0078) | (0.0138) | (0.0372) | (0.0373) | (0.0034) | (0.0065) | (0.0058) | (0.0024) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Y | Y | Y | Υ | Υ | Υ | Y |
| N (obs.) | 13058 | 13058 | 13058 | 13058 | 13058 | 13058 | 13058 | 13058 |
| N (firms) | 5631 | 5631 | 5631 | 5631 | 5631 | 5631 | 5631 | 5631 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0758 | 0.0376 | 0.0288 | 0.0048 | 0.0460 | 0.0563 | 0.0223 | 0.0417 |
| RSS | 2112 | 21988 | 120664 | 208112 | 1025 | 3002 | 2344 | 434 |

Table A5: Effects of forecast errors and forecast growth on firm performance, according to managerial skill (defined as top 1% earners)

Notes: In each column, the dependent variable is the change between the averages of each 3-year period. Standard errors are clustered at firm-level. *10% level of significance, **5% level of significance, **1% level of significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--------------------------|----------------|----------------|---------------------------|-----------------------------------|----------------|----------------|---------------------|---------------|
| Dep. variable: | log sales | log exports | $\log (1 + inv.)$ | $\log (1 + inv.)$ | log | log value | log value | log avg. |
| | | | fixed tangible assets) | $ intangible \\ assets) $ | employment | added | added per worker | worker pay |
| Weighted forecast error | 0.0166*** | 0.0574^{***} | 0.0526*** | -0.0312* | 0.0076*** | 0.0178*** | 0.0097*** | 0.0020** |
| | (0.0022) | (0.0068) | (0.0158) | (0.0175) | (0.0014) | (0.0026) | (0.0024) | (0.0010) |
| Weighted forecast growth | 0.0156^{***} | 0.0487^{***} | 0.0463^{***} | -0.0161 | 0.0055^{***} | 0.0148^{***} | 0.0091^{***} | 0.0014^{**} |
| | (0.0014) | (0.0045) | (0.0107) | (0.0123) | (0.0009) | (0.0017) | (0.0016) | (0.0007) |
| Period x region FE | Y | Y | Y | Y | Υ | Y | Y | Υ |
| Period x industry FE | Υ | Υ | Y | Υ | Υ | Υ | Y | Υ |
| N (obs.) | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 |
| N (firms) | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 |
| $Adj. R^2$ | 0.0825 | 0.0282 | 0.0270 | 0.0076 | 0.0457 | 0.0598 | 0.0256 | 0.0249 |
| RSS | 3937 | 41461 | 202874 | 377977 | 2119 | 5716 | 4491 | 885 |

Table A6: Effects of forecast errors and forecast growth on firm performance using shares of total exports in the forecast error weights

Notes: In each column, the dependent variable is the change between the average of each 3-year period. Standard errors are clustered at the firm-level. *10% level of significance, **5% level of significance, **1% level of significance.

Table A7: Effects of forecast errors and forecast growth on worker compensation using shares of total exports in the forecast error weights

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|--------------------------|------------|-----------|-------------|-------------|----------------|------------|-----------|
| Dep. variable: | log | log hourly | log | $\log (1 +$ | $\log (1 +$ | log total | share with | person FE |
| | $\operatorname{monthly}$ | wage | monthly | overtime | other pay) | hours | a degree | |
| | wage | | base wage | pay) | | | | |
| Weighted forecast error | 0.0022** | 0.0022** | 0.0011 | 0.0091** | 0.0080 | 0.0078*** | 0.0001 | -0.0065* |
| | (0.0010) | (0.0010) | (0.0007) | (0.0040) | (0.0060) | (0.0018) | (0.0005) | (0.0039) |
| Weighted forecast growth | 0.0015^{**} | 0.0014** | 0.0004 | 0.0067** | 0.0057 | 0.0056^{***} | -0.0001 | -0.0017 |
| | (0.0006) | (0.0006) | (0.0005) | (0.0027) | (0.0038) | (0.0012) | (0.0003) | (0.0027) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Y | Υ | Υ | Υ | Υ | Y | Υ | Υ |
| N (obs.) | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 22199 | 12631 |
| N (firms) | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 9306 | 6012 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0121 | 0.0131 | 0.0339 | 0.0198 | 0.0018 | 0.0342 | 0.0073 | 0.0223 |
| RSS | 799 | 798 | 444 | 21877 | 28275 | 3625 | 194 | 3150 |

Notes: In each column, the dependent variable is the change between the averages of each 3-year period. Standard errors are clustered at firm-level. *10% level of significance, **5% level of significance, **1% level of significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|----------------|----------------|---------------------------|-------------|----------------|---------------|----------------|---------------|
| Dep. variable: | log sales | log exports | $\log (1 +$ | $\log (1 +$ | \log | log value | log value | log avg. |
| | | | inv. fixed | inv. | employmen | added | added per | worker pay |
| | | | $\operatorname{tangible}$ | intangible | t | | worker | |
| A. Positive GDP Growth | | | | | | | | |
| Weighted forecast error | 0.0112 | 0.1043^{***} | -0.0511 | 0.0666 | 0.0098* | 0.0001 | 0.0114 | 0.0091^{**} |
| | (0.0148) | (0.0196) | (0.0677) | (0.0636) | (0.0058) | (0.0106) | (0.0116) | (0.0044) |
| Weighted forecast growth | 0.0166^{**} | 0.1164^{***} | 0.0047 | 0.0368 | 0.0040 | 0.0071 | 0.0116^{*} | 0.0039 |
| | (0.0079) | (0.0114) | (0.0390) | (0.0386) | (0.0032) | (0.0059) | (0.0064) | (0.0025) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Y | Y | Υ | Y | Υ | Υ | Y |
| N (obs.) | 14617 | 14617 | 14617 | 14617 | 14617 | 14617 | 14617 | 14617 |
| N (firms) | 7530 | 7530 | 7530 | 7530 | 7530 | 7530 | 7530 | 7530 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0994 | 0.0307 | 0.0313 | 0.0092 | 0.0546 | 0.0341 | 0.0694 | 0.0265 |
| RSS | 2221 | 21377 | 123469 | 241701 | 1255 | 2557 | 3267 | 566 |
| B. Negative GDP Growth | | | | | | | | |
| Weighted forecast error | 0.0987^{***} | -0.0418 | 0.0975 | 0.0498 | -0.0037 | 0.0729^{**} | 0.0687^{**} | 0.0126 |
| | (0.0291) | (0.0596) | (0.1824) | (0.1864) | (0.0205) | (0.0305) | (0.0308) | (0.0162) |
| Weighted forecast growth | 0.0618^{***} | 0.1579^{***} | 0.2304^{***} | 0.1035 | 0.0288^{***} | 0.0018 | 0.0358^{***} | 0.0006 |
| | (0.0119) | (0.0248) | (0.0681) | (0.0780) | (0.0077) | (0.0118) | (0.0117) | (0.0045) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Y | Υ | Υ | Υ | Υ | Υ | Υ | Y |
| N (obs.) | 4652 | 4652 | 4652 | 4652 | 4652 | 4652 | 4652 | 4652 |
| N (firms) | 3354 | 3354 | 3354 | 3354 | 3354 | 3354 | 3354 | 3354 |
| $Adj. R^2$ | 0.0789 | 0.0853 | 0.0183 | 0.00662 | 0.0552 | 0.0157 | 0.0439 | 0.0235 |
| RSS | 982 | 5813 | 37281 | 88401 | 481 | 1063 | 1337 | 178 |

Table A8: Effects of forecast errors and forecast growth on firm performance in years with positive vs negative GDP growth

Notes: In each column, the dependent variable is the change between the average of each 3-year period. Standard errors are clustered at the firm-level. *10% level of significance, **5% level of significance, ***1% level of significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|--------------|------------|--------------------------|-------------|-------------|-----------|------------|-----------|
| Dep. variable: | log | log hourly | log | $\log (1 +$ | $\log (1 +$ | log total | share with | person FE |
| | monthly | wage | $\operatorname{monthly}$ | overtime | other pay) | hours | a degree | |
| | wage | | base wage | pav) | | | | |
| A. Positive GDP Growth | | | | | | | | |
| Weighted forecast error | 0.0060^{*} | 0.0054 | 0.0058^{**} | 0.0193 | 0.0167 | 0.0089 | 0.0006 | -0.0008 |
| | (0.0035) | (0.0035) | (0.0028) | (0.0162) | (0.0206) | (0.0071) | (0.0024) | (0.0207) |
| Weighted forecast growth | 0.0019 | 0.0018 | 0.0013 | 0.0108 | 0.0025 | 0.0018 | 0.0003 | 0.0038 |
| | (0.0019) | (0.0019) | (0.0015) | (0.0098) | (0.0118) | (0.0040) | (0.0013) | (0.0105) |
| Period x region FE | Υ | Y | Y | Υ | Y | Υ | Y | Y |
| Period x industry FE | Y | Y | Υ | Y | Υ | Y | Y | Y |
| N (obs.) | 14617 | 14617 | 14617 | 14617 | 14617 | 14617 | 14617 | 8404 |
| N (firms) | 7530 | 7530 | 7530 | 7530 | 7530 | 7530 | 7530 | 4795 |
| Adj. \mathbb{R}^2 | 0.0148 | 0.0167 | 0.0418 | 0.0216 | 0.0002 | 0.0377 | 0.0070 | 0.0237 |
| RSS | 495 | 493 | 267 | 14059 | 17576 | 2129 | 118 | 2086 |
| B. Negative GDP Growth | | | | | | | | |
| Weighted forecast error | 0.0080 | 0.0095 | 0.0081 | -0.0330 | -0.0962 | 0.0155 | -0.0020 | -0.0517 |
| - | (0.0118) | (0.0115) | (0.0079) | (0.0543) | (0.0663) | (0.0207) | (0.0053) | (0.0326) |
| Weighted forecast growth | 0.0034 | 0.0034 | -0.0004 | 0.0111 | 0.0273 | 0.0268*** | -0.0017 | -0.0160 |
| | (0.0049) | (0.0049) | (0.0032) | (0.0211) | (0.0250) | (0.0090) | (0.0021) | (0.0119) |
| Period x region FE | Υ | Y | Y | Υ | Y | Υ | Υ | Y |
| Period x industry FE | Υ | Y | Υ | Y | Y | Υ | Υ | Y |
| N (obs.) | 4652 | 4652 | 4652 | 4652 | 4652 | 4652 | 4652 | 2853 |
| N (firms) | 3354 | 3354 | 3354 | 3354 | 3354 | 3354 | 3354 | 2099 |
| $\operatorname{Adj.} \operatorname{R}^2$ | -0.0006 | -0.0009 | 0.0055 | 0.0197 | -0.0035 | 0.0372 | 0.0110 | 0.0343 |
| RSS | 161 | 161 | 100 | 5050 | 5471 | 889 | 38 | 537 |

Table A9: Effects of forecast errors and forecast growth on worker compensation in years with positive vs negative GDP growth

Notes: In each column, the dependent variable is the change between the averages of each 3-year period. Standard errors are clustered at firm-level. *10% level of significance, **5% level of significance, ***1% level of significance.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--|-----------|-------------|-------------------|-------------------|------------|-----------|-----------|------------|
| Dep. variable: | log sales | log exports | $\log (1 + inv.)$ | $\log (1 + inv.)$ | \log | log value | log value | log avg. |
| | | | fixed tangible | intangible | employment | added | added per | worker pay |
| | | | assets) | assets) | | | worker | |
| Weighted forecast error | 0.0680*** | 0.1372*** | 0.0637 | 0.1048** | 0.0224*** | 0.0420*** | 0.0654*** | 0.0039 |
| | (0.0082) | (0.0141) | (0.0469) | (0.0483) | (0.0049) | (0.0085) | (0.0092) | (0.0038) |
| Weighted forecast growth | 0.0468*** | 0.1208*** | 0.0547^{**} | 0.0703** | 0.0097*** | 0.0263*** | 0.0380*** | -0.0022 |
| | (0.0042) | (0.0085) | (0.0266) | (0.0287) | (0.0024) | (0.0043) | (0.0047) | (0.0020) |
| Period x region FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Period x industry FE | Υ | Υ | Υ | Υ | Υ | Υ | Υ | Υ |
| N (obs.) | 22186 | 22186 | 22186 | 22186 | 22186 | 22186 | 22186 | 22186 |
| N (firms) | 9302 | 9302 | 9302 | 9302 | 9302 | 9302 | 9302 | 9302 |
| $\operatorname{Adj.} \operatorname{R}^2$ | 0.0765 | 0.0309 | 0.0275 | 0.0076 | 0.0442 | 0.0260 | 0.0573 | 0.0602 |
| RSS | 3567 | 39188 | 170838 | 371225 | 2026 | 4075 | 5340 | 914 |

Table A10: Effects of forecast errors and forecast growth on firm performance, no lagged variables

Notes: In each column, the dependent variable is the change between the average of each 3-year period. Standard errors are clustered at the firm-level. *10% level of significance, **5% level of significance, ***1% level of significance.

A.2 Appendix Figures

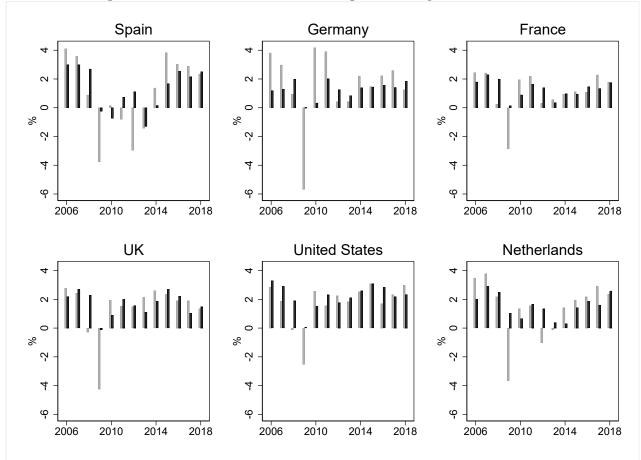


Figure A1: Actual and forecasted GDP growth in top destinations

Notes: Figure depicts actual GDP growth (gray bars) and forecast GDP growth (black bars) for the six most important export destinations in 2006.

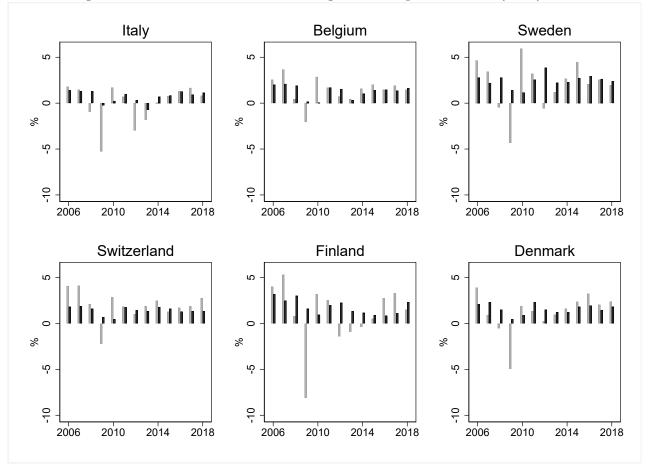


Figure A1: Actual and forecasted GDP growth in top destinations (cont.)

Notes: Figure depicts actual GDP growth (gray bars) and forecast GDP growth (black bars) for the seventh to twelfth most important export destinations in 2006.

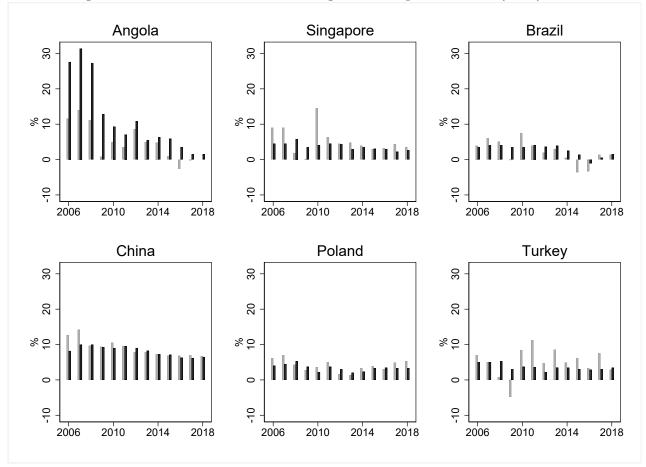
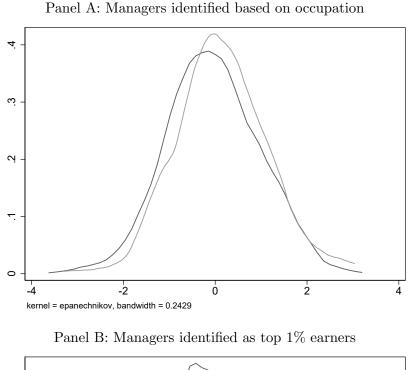
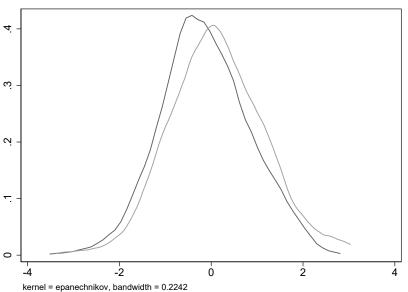


Figure A1: Actual and forecasted GDP growth in top destinations (cont.)

Notes: Figure depicts actual GDP growth (gray bars) and forecast GDP growth (black bars) for the thirteenth to eighteenth most important export destinations in 2006.

Figure A2: Z-score of firms with high and low-skilled managers, 2016





Notes: Figure depicts the distribution of standardised values of Z-scores of firms with high share of managers with a degree (in gray) versus firms with a low share of managers with a degree (in black). High versus low shares are defined as above versus below the median. In Panel A, managers are identified based on occupation while in Panel B managers are identified as the top 1% earners.

A.3 Data sources and description

In this Appendix, we provide further details about the data sets used in the empirical analysis. We combine and examine several sources of panel data from Portugal spanning the period 2006-2018. We provide a brief description of each data source in this section and give further details in Appendix A.3.

Employer-employee data: Quadros de Pessoal (QP) [Personnel Records] is a compulsory census run by the Ministry of Employment covering the population of firms with wage earners in manufacturing and services. Each firm is required by law to provide information on an annual basis about its characteristics and those of each individual that comprises its workforce. Firm-level information includes annual sales, number of employees, industry code, geographical location, date of constitution and percentage of capital that is foreign-owned. The industry code is defined at the 5-digit level of the National Classification of Economic Activities (CAE). The set of worker characteristics includes wages (monthly base wage, overtime pay, and other regular and irregular components of pay), gender, age, schooling, date of starting, detailed occupation and hours worked. A worker may also be matched to the firm. An important feature of these data is that particular care is placed on the reliability of the information. Indeed, the data are used by the Ministry of Employment for checking the employer's compliance with labour law. Moreover, Portuguese law makes it compulsory for firms to make this information available to every worker in a public place of the establishment. Extensive checks have been performed to guarantee the accuracy of worker and firm data. After these checks, we kept for analysis full-time wage earners working at least 100 hours a week, aged between 20 and 60 years old.

Firm census: Using common unique firm identifiers, we supplement the firm-year data from QP with information from the *Sistema de Contas Integradas das Empresas (SCIE)* [Enterprise Integrated Accounts System], a yearly census of firms run by National Statistics Institute (INE). Since 2006, the main source of the census is administrative data from Simplified Information on Enterprises, which consists of fiscal, accounting and statistical information provided by firms through a single form transmitted electronically through www.portaldasfinancas.gov.pt. By filing this form, firms fulfil four different legal obligations: the annual statement of fiscal and accounting information, the accounts registry, the provision of statistical information to INE, the provision of information of annual accounts data for statistical purposes to the Bank of Portugal, and the provision of statistical information to the General Directorate of Economic Activity of the Ministry of the Economy in the context of the legal regime for access and provision of activities of commerce, services and hospitality. The main objective of SCIE is to

characterise the economic and financial behaviour of firms, through a set of relevant variables for the corporate sector, as well as financial ratios, which are commonly used in the financial analysis of firms. This data set includes information on total sales, investment, total employment, wage bill, industry, location, among several other variables.

International trade statistics: We merge the above data sets with yearly data on firms' export transactions from *Estatsticas do Comrcio Internacional (ECI)* [Foreign Trade Statistics] from INE. This is the country's official information source on imports and exports. It comprises the export flows of virtually all exporting firms, and provides detailed information on the product exported, the destination market, and the value and quantity exported. These data are collected through two different systems. Information on trade with countries outside the EU (external trade) is obtained from the customs clearance system, which covers the universe of external trade transactions. The data on the transactions with other EU member States (internal trade) are collected through a separate survey called the Intrastat. In this case, the information providers are companies engaged in internal trade and registered in the VAT system whose value of annual shipments exceeds a given statistical threshold. This (legally binding) cut-off is defined by each member state so that as many of the smallest exporters as possible are exempted from submitting statistical declarations, while the quality standard of the statistics remains adequate. Exported products are classified according to the eight-digit level of the Combined Nomenclature (CN). This is the most detailed product classification system for foreign trade statistics in the EU. Export values in these data are free-on-board, thus excluding any duties or shipping charges.

Management practices survey: We further use data from *Inquito s Pricas de Gesto* (*IPG*) [Management Practices Survey] for 2016. IPG is a non-periodical survey conducted by INE, which collects information on the perceptions of top managers about the management practices of their firms. The 2016 survey was the first and only of its kind collected in Portugal. It seeks to evaluate the importance of management practices for firm productivity, as well as other key indicators that make it possible to evaluate differences in productivity between Portuguese firms. IPG employed a stratified sample of firms operating in Portugal covering the whole non-financial private sector in 2016, excluding micro firms (with less than five employees). The sample is representative by sector (20 sectors corresponding of aggregations of the 2-digit level of the CAE), firm size and age, as well as belonging (or not) to a conglomerate. The IPG survey was an electronic survey targeted at managers, who are typically senior enough to have a good understanding of management practices. These protocols helped yield a 86.7% response rate. The survey includes questions that make it possible to evaluate management practices in three main areas: (1) Strategy, monitoring and information; (2) Human Resources; and

(3) Management and social responsibility systems. We selected questions on 18 management practices that are closely related to those adopted in Bloom and Reenen (2007). First, we classified the 18 practices into 4 categories: operational (2 practices), targets (4 practices), monitoring (10 practices) and incentives (2 practices). Following their approach, our measure of management quality was constructed by z-scoring (normalising to mean 0, standard deviation 1) the 18 individual questions in IPG, averaging them, and then z-scoring the average. This process yields a management practice score with mean 0 and standard deviation 1.

Actual and forecasted GDP growth: We further use yearly information on actual and recently forecasted GDP growth from the World Economic Outlook (WEO) of the International Monetary Fund (IMF). WEO is usually published twice a year (in April and September/October). It presents IMF staff economists' analyses of global economic developments during the near and medium term. The WEO database is created during the biannual WEO exercise, which begins in January and June of each year and results in the April and September/October WEO publication. Selected series from the publication, including actual and forecasted GDP growth are available in a database format at https://www.imf.org/en/Publications/SPROLLs/ world-economic-outlook-databases. Every April and October, the WEO provides yearahead and current-year GDP growth forecasts. We refer to the year for which the forecast is being made as the target year. Forecasts made in the fall WEO before the target year are called year-ahead forecasts and those made during the Spring target year are called current-year forecasts. During our sample period, forecast data are available for 195 countries. After merging these data with ECI we were left with 174 destinations, which account for 99.7% of all exports in 2006. Table A2 reports the export shares to the main destinations in 2006, both in the full ECI data and in the estimation sample.

A.4 Variable definitions in the econometric analysis

This section describes the variables used in the econometric analysis and the corresponding sources:

Sales: Total value of sales (in Portugal and abroad) during the reference year. Source: SCIE.

Exports: Export revenue of a firm during the reference year. Source: ECI.

Investment in fixed tangible assets: Investment in fixed tangible assets during the reference year. Source: SCIE.

- Investment in intangible assets: Investment in intangible assets during the reference year. Source: SCIE.
- Employment: Number of employees during the reference year. Source: SCIE.
- *Value added*: Value added created by a firm during the reference year evaluated at market prices. Source: SCIE.
- Share of foreign-owned capital: Share of capital that is foreign-owned in current year. Source: QP.
- Share of state-owned capital: Share of capital that is state-owned in current year. Source: QP.

Firm age: Number of years passed since a firm was first registered in Portugal. Source: QP.

- Exporter: Indicator variable =1 if firms records some export revenue in reference year. Source: ECI.
- *Export to sales ratio*: Ratio between exports and total sales in reference year. Sources: ECI and SCIE.
- *Number of destinations served*: Number of different export destinations served by a firm during the reference year. Source: ECI.
- Weighted forecast error: Weighted difference between observed GDP growth in destinations and growth forecast for that destination in the Spring edition of the WEO of the IMF (weighs: share of exports to that destination in 2006). Sources: ECI and IMF.
- Weighted forecast growth: Weighted growth forecast for destinations in the Spring edition of the WEO of the IMF (weighs: share of exports to that destination in 2006). Sources: ECI and IMF.
- Avg. labor costs: Ratio between the wage bill (including wages, social security contributions, benefits, etc.) and the number of paid employees. It corresponds to the average gross earnings per paid worker. Source: SCIE.
- Avg. monthly wage: Average monthly wage. Source: QP.
- Avg. hourly wage: Average hourly wage. Source: QP.
- Avg. monthly base wage: Average monthly base wage. Source: QP.

Avg. overtime pay: Average overtime pay. Source: QP.

Avg. other pay: Average other components of pay. Source: QP.

Total hours: Total hours worked by employees at the firm. Source: QP.

Share with a degree: Share of workers with higher education. Source: QP.

- Avg. person fixed effects: Average estimated person effect using AKM models. Source: QP.
- Mean employee ability: Average estimated person effect of non-managerial employees using AKM models. Source: QP.
- Mean manager ability: Average estimated person effects of top managers using AKM models. Source: QP.
- Share of female employees: Share of female employees in reference year. Source: QP.
- Share of high-skill managers: Share of workers with higher education. Managers defined as workers in top fifth percentile of wage distribution. Source: QP.
- Share of employees for which fixed effects were computed (raised to the power of 3): Share of workers in connected firms. Source: QP.

All monetary variables are in euros and have been deflated to constant 2018 prices using the Portuguese GDP deflator or the CPI Index (for wages) from INE.