Heterogeneous Firm Expectations and Misallocation

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Abstract

This paper examines how heterogeneity in firms' forecasting accuracy contributes to resource misallocation. Using French quarterly survey data on firm expectations matched with administrative data, we show that firms make forecast errors that significantly affect investment and hiring decisions. These decisions, in turn, lead to differences in marginal revenue product of capital (MRPK) and labor (MRPL). Heterogeneity in forecasting accuracy thus generates dispersion in MRPK and MRPL. We show that when firms underpredict their demand, their MRPK increases by 5.4% and MRPL by 4.1% compared to when they forecast their demand accurately. These effects are persistent over time and do not only reflect the existence of idiosyncratic shocks.

Keywords: Heterogeneous firms, Capital misallocation, Forecast errors.
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"The outstanding fact is the extreme precariousness of the basis of knowledge on which our estimates of prospective yield have to be made. Our knowledge of the factors which will govern the yield of an investment some years hence is usually very slight and often negligible." Keynes (1936)

1 Introduction

In standard macroeconomic models, firms are forward-looking and base their decisions on expectations about the future. For instance, they invest until the marginal cost of capital equals the expected marginal return. However, if these expectations turn out to be incorrect, the resulting decisions are ex post suboptimal. Recent empirical evidence shows that firms' managers frequently rely on forecasts that later prove inaccurate. Dispersion in forecasting accuracy across firms can therefore lead to heterogeneity in marginal returns and a misallocation of resources, with potentially significant consequences for aggregate productivity and output. Yet, the extent to which firms' forecast errors contribute to resource misallocation remains largely unexplored.

In this paper, using detailed firm-level data for French firms, we document that the observed dispersion in firms' marginal revenue products of capital (MRPK) and labor (MRPL) across firms (which is a common metric for resource misallocation) is related to heterogeneity in firms' forecast accuracy. Specifically, we show that firms with less accurate (optimistic or pessimistic) expectations about their own demand are more likely to make suboptimal investment and hiring decisions, which in turn contributes to a dispersion in firms' marginal revenue products of factors.

To establish this relationship, we match a rich quarterly panel survey of French firms' expectations with firm-level balance sheet data, enabling us to directly analyze the link between expectation errors and factor misallocation. Our analysis is based on the *Enquête trimestrielle de Conjoncture dans l'Industrie* (ECI), a mandatory quarterly survey of French industrial firms conducted since 1992. This survey asks business leaders their qualitative expectations for a large set of variables – including firm-specific demand, production, prices, and employment – but also their subsequent realizations, allowing us to identify expectation errors ex post. The long panel structure of the data offers a unique opportunity to investigate the process of expectation formation over an extended time horizon. We match this survey data with *FICUS* and *FARE*, comprehensive administrative datasets derived from firms' tax filings that cover the universe of non-financial French firms. This combination enables us to compute firms' marginal revenue products of capital and labor and to examine how these relate to expectation errors within narrowly defined industries. We end up with a sample of over 6,000 manufacturing firms across 29 different 2-digit sectors and 236 4-digit sectors, allowing us to compare productivity across similar firms.

Before examining how dispersion in MRPK and MRPL relates to forecasting errors made by firm managers, we first explore two key conditions that must be met for forecast errors to affect the marginal revenue products of inputs. First, managers should provide sensible responses to the survey. Second, firms' expectations should matter for their decisions. Our empirical findings confirm that these two necessary conditions are met by our sample of firms. First, we provide strong evidence of both the external validity of survey responses against administrative data and the internal consistency of firms' answers to the survey, suggesting that firms' reported expectations reflect meaningful assessments of their business conditions. Second, we document reduced-form evidence showing that firms' expectations about their own demand are significantly correlated with their investment and employment decisions. Firms expecting an increase in their demand tend to experience a higher actual growth of production or investment than firms expecting stable demand. Similarly, firms expecting a decline in demand reduce their employment relative to firms expecting stable demand.

We then provide firm-level evidence that demand forecast errors correlate significantly with marginal revenue product of capital and labor. Our baseline estimates indicate that when firms underpredict their demand, their MRPK increases by 5.4% and their MRPL by 4.1%. Our results are obtained using reduced-form regressions. However, we show that this significant relationship holds even after controlling for possible confounding factors. In particular, we run regressions controlling for firm fixed effects, sector-by-year fixed effects, and time-varying firm characteristics and we show that the effects are robust across increasingly fine-grained industry classifications, comparing firms within narrowly defined 4-digit sectors facing almost identical market conditions. Moreover, using the large set of questions asked in the firm survey, we show that our results remain robust when we include controls for key drivers of misallocation often cited in the literature such as financial frictions, labor market rigidities and capital adjustment costs but also when we control for the general forecast ability of firms. We also estimate the extent to which demand forecast errors contribute to TFP losses from misallocation. We find that the TFP loss related to demand forecast errors is about 11% of the TFP loss of financial constraints, one-quarter of the TFP loss from obstacles to capital adjustments, and twice the TFP loss from obstacles to labor adjustments.

We interpret this dispersion as inefficient and therefore as evidence of misallocation for two reasons. First, the effect of forecast errors on firms' MRPK and MRPL persists for five and four years, respectively, indicating that firms fail to reallocate resources efficiently even after new information becomes available. Second, to confirm that the results are not driven solely by efficient dispersion arising from idiosyncratic shocks, we repeat our analysis using the component of the forecast error explained by deviations from firms' rational expectations rather than by idiosyncratic shocks. Specifically, we decompose forecast errors into predictable components—systematic deviations from rational expectations—and unpredictable components, which reflect shocks. We find that both components of the demand forecast errors contribute significantly to misallocation.

Finally, using a survey of the exact same firms about their quantitative investment outlook, the *Enquête de Conjoncture sur les Investissements dans l'Industrie* (ECII), we are also able to document the channel through which expectations errors might affect MRPK and MRPL. When firms expect an increase in their demand, they invest and hire more to expand their production capacity. If actual demand falls short of expectations, firms end up with excessive capital and payroll relative to their peers, resulting in lower MRPK and MRPL. Conversely, pessimistic firms that under-predict demand under-invest and under-hire, leading to higher MRPK and MRPL. In addition, we provide direct evidence that ex post forecast errors are correlated with firms' investment and hiring decisions. Finally, we show that the share of investment and employment decisions that can be retrospectively attributed to incorrect demand forecasts is strongly negatively correlated with firms' MRPK and MRPL.

Our work contributes to the literature on the sources of factor misallocation, building on the seminal works of Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and Banerjee and Moll (2010). The literature has highlighted the importance of misallocation and its consequences for aggregate productivity and output. Among the various sources of misallocation, the most extensively studied are financial frictions (Buera and Shin 2013, Hopenhayn 2014, Midrigan and Xu 2014, Karabarbounis and Macnamara 2021, Su 2024, among others) and labor market frictions (Alpysbayeva and Vanormelingen 2022, Bilal et al. 2022, Heise and Porzio 2022, among others). Other strands of research emphasize the role of adjustment costs and idiosyncratic shocks (Cooper and Haltiwanger 2006, Asker, Collard-Wexler, and De Loecker 2014, Moll 2014, Decker et al. 2020), macroeconomic risks (David, Schmid, and Zeke 2022), regulatory barriers (Aghion et al. 2008), institutional and policy environments (Bartelsman, Haltiwanger, and Scarpetta 2013, Gorodnichenko et al. 2025, among others) and managers skills (Hsieh, Hurst, et al. 2019, Bloom, Codreanu, and Fletcher 2025, Bloom, Iacovone, et al. 2025, among others). This paper's contribution is to show that forecast errors are an additional and significant factor behind the observed dispersion of marginal returns.

A subset of this literature emphasizes the importance of the role of firms' information to explain misallocation. Most of this literature uses proxy to quantify firm uncertainty and imperfect information. For instance, David, Hopenhayn, and Venkateswaran (2016) and David and Venkateswaran (2019) build models showing that capital misallocation can arise when firms choose their level of capital under limited information. Senga (2018) uses the dispersion in earnings forecasts by analysts to assess the uncertainty faced by firms. Our firm survey data allow us to directly observe firms' expectations, their realizations and identify the nature of firms' forecast errors. We can also directly observe the impact of these errors on firms' factor productivity. In addition, the rich set of information contained in these datasets allows us to compare our findings with alternative factors traditionally highlighted in the literature such as financial frictions, labor market frictions or managers' skills.

The papers closest to ours are Tanaka et al. (2020), Barrero (2022), Ropele, Gorodnichenko, and Coibion (2024) and Ma et al. (2024). Barrero (2022) and Ma et al. (2024) measure distortions in firms' forecasts but interpret their effects on firm decisions through the lens of a structural model. Tanaka et al. (2020) and Ropele, Gorodnichenko, and Coibion (2024) document that firms' expectations of aggregate conditions (GDP and inflation, respectively) affect the dispersion of realized returns. In contrast, we observe firms' expectations of their own conditions and provide direct evidence of the impact of firms' *own demand* expectation errors on capital and labor misallocation. We are also able to document the underlying mechanism through which these errors affect firms' factor allocation decisions.

Our paper also relates to the literature on firms' expectations, which has documented systematic deviations from rational expectations across various dimensions.[1] Born, Enders, and Müller (2023) provide a comprehensive survey of this literature, which includes papers by Bachmann and Elstner (2015), Massenot and Pettinicchi (2018), Boneva et al. (2020), Ma et al. (2024), Born, Enders, Menkhoff, et al. (2024) and Bloom, Codreanu, and Fletcher (2025) among others. It also connects to the strand of this literature showing that firms act on their expectations (Coibion, Gorodnichenko, and Ropele 2020, or Enders, Hünnekes, and Müller 2022). Our findings contribute to this literature by showing that deviations from rational expectations affect firm decisions, leading to long-lasting impacts on firm performance.

The remainder of the paper is organized as follows. Section 2 describes the data sources and the construction of our main variables of interest. Section 3 outlines two fundamental stylized facts about expectation formation, which are key for understanding how forecast errors can influence MRPK and MPRL. Section 4 analyzes how forecast errors correlate with observed MRPK and MRPL. Section 5 presents supporting evidence for the proposed mechanism. Section 6 concludes.

2 Data and Measurement

This paper investigates, at the firm level, the relationship between the marginal revenue products of capital and labor (MRPK and MRPL) and firms' forecast errors about their demand. To do so, we combine two high-quality firm-level datasets. The first is a balance-sheet dataset covering the universe of French firms, which we use to measure MRPK and MRPL. The second is a large survey dataset that collects managers' expectations and realizations for several variables in firms operating in the manufacturing sector, which we use to measure forecast errors.[2] This section describes the datasets and explains how we construct our main variables of interest.

2.1 Misallocation

Resource misallocation is commonly defined as the observed dispersion in firms' factor returns and two key metrics can be used to measure these returns: the marginal revenue product of capital (MRPK) and the marginal revenue product of labor (MRPL). We compute firms' MRPK as the logarithm of value added over fixed tangible capital ($\log \frac{VA_t}{K_t}$) and firms' MRPL as the logarithm of value added over total compensation of employees ($\log \frac{VA_t}{W_t}$).[3] Following

[1] This literature builds on works showing the key role of information issues in macroeconomic dynamics (Angeletos and Lian 2016, Angeletos, Huo, and Sastry 2021) and data-driven decision making in firm performance (Brynjolfsson and McElheran 2016).

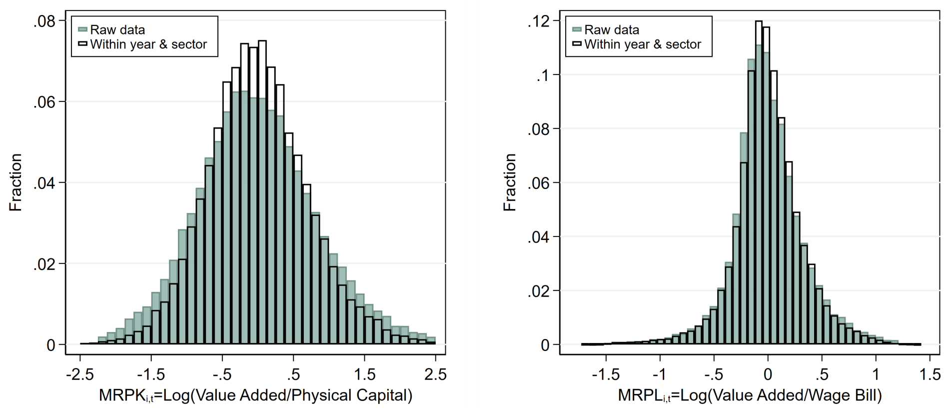
[2] These datasets are firm-level confidential data. They are made available for research purposes upon approval by the *Comité du Secret Statistique* and are accessible through the CASD – *Centre d'accès sécurisé aux données*.

[3] As robustness analysis, we provide results where we use different measures of K and L to ensure that our results are not driven by a specific definition of these variables. We construct alternative measures of MRPK using net

standard practice in the literature (Hsieh and Klenow 2009, Bau and Matray 2023, or Albrizio, González, and Khametshin 2023), we use average returns as proxies for marginal returns, as they differ only by a constant factor under standard production function assumptions.[4]

These calculations rely on FICUS and FARE, two comprehensive administrative databases constructed from firms' annual profit declarations to the French tax authorities. These databases, starting in 1994, cover the universe of non-financial French firms and provide detailed balance sheet and income statement information, allowing for precise measurement of value added, capital stocks and labor costs. Appendix Table A1 describes the data used and Appendix Figure A1 plots the distribution of the key characteristics of our sample of firms (age, capital, leverage and employment).

Figure 1: Distribution of MRPK and MRPL



Note: This figure shows the (mean-centered at zero) distribution of MRPK (left panel) and MRPL (right panel), using raw data (green bars) and MRPK and MRPL net of year and sector fixed effects (white bars) for all firms present in the ECI survey from 1994 to 2019.

Figure 1 presents two key visualizations of capital and labor misallocation in France from 1994 to 2019. The left panel shows the distribution of MRPK, while the right panel displays the distribution of MRPL. In both panels, the green-tinted histograms represent the raw data (mean-centered), while the white histograms show the distributions after removing year and sector fixed effects. The residual dispersion after accounting for sector and year fixed effects represents what is typically characterized as misallocation: firms with similar characteristics operating in the same sector and year should theoretically have similar marginal returns to factors of production.[5]

The dispersion in both distributions indicates misallocation in the French economy. For MRPK, the within-sector-year standard deviation is approximately 0.85 log points, suggesting

fixed tangible capital and capital including leased assets. Similarly, we build an alternative measure of L based on the number of employees. See Appendix A for a description of the variables used.

[4]Our balance sheet data are measured at the firm level, not the plant level, so one limitation is that we cannot implement the correction for potential measurement error in marginal revenue products that exploits how revenue growth responds to input growth within firms across plants (see Bils, Klenow, and Ruane 2021).

[5]Appendix Figure A2 plots the evolution over time of the average across sectors of the standard deviation of MRPK and MRPL within sectors.

that a firm at the 75^{th} percentile of the distribution has a marginal revenue product of capital roughly three times as high as a firm at the 25^{th} percentile within the same sector and year. The within-sector-year dispersion in MRPL is somewhat lower (0.34 log points) but also shows that some firms generate substantially more value from an additional euro spent on labor than others.[6]

The observed dispersion in marginal returns may arise from different sources. A key question we address in the following sections is whether heterogeneity in firms' forecast errors contributes to this misallocation.

2.2 Forecast errors

We derive firms' expectation errors from the Quarterly Survey of Economic Conditions in the Industry (*ECI: Enquête Trimestrielle de Conjoncture dans l'Industrie*) and the Quarterly Survey of Investment Conditions in the Industry (*ECII: Enquête de Conjoncture sur les Investissements dans l'Industrie*). These two surveys are conducted by the French statistical office (*INSEE - Institut National de la Statistique et des Études Économiques*) among the exact same sample of manufacturing firms.[7] As mandatory quarterly surveys conducted since 1992, they provide a uniquely rich longitudinal dataset on firm expectations in France.

Firms are sampled from an exhaustive source covering the universe of firms with more than 20 employees in the manufacturing sector. The sampling is stratified by workforce size and economic sector, with firms exceeding 500 employees or 150 million euros in annual turnover systematically included, thereby ensuring national representativeness. The average response rate is significantly higher than typical voluntary business surveys (about 80%). This high response rate minimizes selection concerns that might otherwise bias analysis of expectation patterns. Moreover, to aggregate our measures at the yearly frequency, we keep only firms providing answers to the survey in all four quarterly waves in a given year.

On average, in the final sample we consider (1994–2019), 1 500 firms report per quarter, and the panel nature of the data is substantial - firms remain in the sample for an average of 23 quarters, allowing us to track expectation formation processes over extended periods (see also Andrade et al. (2022) for an extensive description of this survey). We present in Appendix Figure A3 the distribution of the number of years firms are observed in these surveys. This longitudinal aspect is crucial because it allows us to distinguish systematic firm-specific biases from time-varying forecast errors for a given firm, leading to a more precise assessment of their effects.

[6] To benchmark the magnitude of misallocation in France relative to other countries, Gorodnichenko et al. (2025) provide a cross-country comparison for Europe, though based on a different sample of firms (across all sectors of Orbis data). They find similar dispersions of MRPK and MRPL with their sample of French firms.

[7] The survey is addressed to firms' CEOs or CFOs, and respondents are required to disclose their position and identity when completing it (these variables are however not available to researchers). The survey states that intentionally inaccurate responses are punishable by law with a fine. Consistency checks on administrative data are performed to ensure the coherence of total turnover, turnover by product, number of employees, and year-to-year changes in these variables. Questionnaires displaying anomalies are subject to manual review.

Most of the questions in the ECI survey are qualitative, and their wording has remained the same since the beginning of our sample period in 1994. Firms report on their expected and realized own demand, production, prices, and employment, as well as their expectations on aggregate production, prices, or wages. Some questions like prices, demand or production are asked for the different main products of the firm.[8] In our sample, about 80% of firms report answers on prices, production or demand only for their main product, while a little less than 20% report answers for more than one product (2.4 products on average).[9] The ECII survey contains both qualitative and quantitative questions about expected and realized investment at the firm level. The quantitative questions about investment are in levels (in euros) at different horizons (previous calendar year, current calendar year and next calendar year). This quantitative dimension complements the qualitative nature of the ECI and allows us to connect firms' qualitative expectations about business conditions with their quantitative investment plans.[10]

Following Bachmann, Elstner, and Sims (2013), we construct expectation errors using qualitative answers. The survey asks firms about the likely evolution of a given variable over the next three months, as well as the evolution during the previous three months. Firms can respond using three qualitative categories of answers: 'increase', 'stable', or 'decrease'. Table A6 in the Appendix provides the distribution of individual answers for the main variables.

For each variable, we compute the expectation error by comparing the realization reported at date t with the forecast of this variable provided in the previous survey wave (i.e. one quarter ago). We define in Equation (1) the forecast error as:

$$x_{i,p,t}^{FE} = x_{i,p,t} - F_{i,p,t-1}x_{i,p,t} \tag{1}$$

where $x_{i,p,t}^{FE}$ is the ex post expectation error for variable x measured for product p in firm i at date t, $x_{i,p,t}$ is the realization of variable x (demand, production, etc.) reported by the manager of firm i for product p at date t, and $F_{i,p,t-1}x_t$ is the forecast for variable x reported at time $t-1$ by firm i for product p and for the horizon t.

Table 1 outlines our classification of these errors. A firm is labeled as 'strongly overpredicting' a variable if it anticipated an increase but the realized outcome was a decrease ($x_{i,p,t}^{FE} = -2$). Symmetrically, a firm is labeled as 'strongly underpredicting' if this firm anticipated a decrease but the outcome was an increase ($x_{i,p,t}^{FE} = 2$). Less extreme errors include 'underpredicting' ($x_{i,p,t}^{FE} = 1$) and 'overpredicting' ($x_{i,p,t}^{FE} = -1$), while forecasts with no error are considered 'accurate' ($x_{i,p,t}^{FE} = 0$).

[8] Products are defined at level 4 of the NACE classification of products/sectors.

[9] Appendix Figure A4 plots the distribution of the number of products for which forecasts are elicited by firms.

[10] Appendix Figures A5 and A6 show the original questions asked in ECI and ECII surveys. Appendix Tables A4 and A5 provide the English translation of these questions.

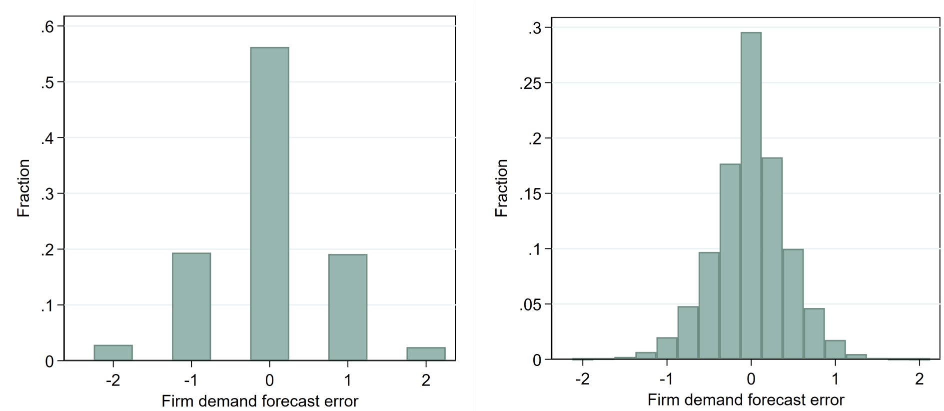
Table 1: Construction of expectation errors

Realized$_t$ / Exp$_{t-1}$	**Decrease**	**Stable**	**Increase**
Decrease	Accurate (0)	Underprediction (1)	Strong Underprediction (2)
Stable	Overprediction (-1)	Accurate (0)	Underprediction (1)
Increase	Strong Overprediction (-2)	Overprediction (-1)	Accurate (0)

Note: Qualitative forecast errors based on expectations and reported outcomes in the ECI survey.

The left panel of Figure 2 displays the distribution of demand expectation errors at the product-quarter level.[11] The distribution is centered around zero, with approximately 55% of forecasts being accurate ($x^{FE}_{i,p,t} = 0$), while about 20% of forecasts are too optimistic and 25% too pessimistic. Since a large share of firms in our sample report demand forecast for multiple products, we aggregate product-level forecast errors to obtain a firm-level measure of the forecast error. For firms producing multiple products, we weight each product's forecast error by its share of the firm's revenues. This weighting ensures that errors on economically significant products contribute more to our firm-level measure than errors on more marginal product lines. This allows us to compute an aggregate expectation error for each firm and quarter. To align the frequency of the survey data with the annual frequency of our balance sheet data, we compute the yearly average of the quarterly expectation errors at the firm level. The right panel of Figure 2 shows the distribution of demand expectation errors at the firm*year level, which by construction displays a more continuous distribution than the product*quarter level distribution.[12]

Figure 2: Distribution of Demand Forecast Errors at Product*Quarter and Firm*Year levels



Note: This figure shows the distribution of firm demand forecast errors at the product*quarter (left panel) and firm*year (right panel) levels. A forecast error equal to 2 means that the firm has strongly underpredicted its own demand (see Table 1 for the definition of forecast errors). Sample period: 1994-2019.

Overall, our forecast error metric provides a granular view of firms' ability to predict their own business conditions. The substantial variation in forecast accuracy, both across firms

[11] Appendix Figure A7 plots the evolution of average forecast errors over time.

[12] We show in Appendix D that our results are robust to the product and time aggregation.

and within firms over time, offers an opportunity to examine how differences in forecasting accuracy relate to economic outcomes such as resource-allocation efficiency.

Once we matched firm-level datasets containing MRPK and MRPL and survey data containing the forecast errors, our final sample contains more than 36 000 observations from more than 6 300 unique firms spanning 1994 to 2019.[13] Firms in our sample have an average capital stock of €62.8 million, total assets of €119.6 million, and employ 375 workers on average. The sample includes firms across different age groups, with a mean age of 39 years and a standard deviation of 25 years, providing sufficient variation to control for life-cycle effects in our analysis. Our sample includes firms from 29 different 2-digit sectors and 236 4-digit sectors, offering rich cross-sectional variation that enables us to compare returns within narrowly defined industries.[14] This sectoral diversity ensures that our findings on the relationship between expectation errors and misallocation are not driven by industry-specific patterns, but represent broader economic factors. By combining these detailed measures of firm-level misallocation with survey-based measures of expectation errors, we can directly document whether firms' forecast errors are associated with observed capital and labor misallocation.

3 Stylised Facts on Firms' Expectation Formation

Two necessary conditions have to be fulfilled for expectations errors of firms' managers to be related to the observed dispersion in marginal revenue products: (1) managers provide meaningful answers to the survey and not trivial answers, and (2) their expectations on their own variables matter for their economic decisions. This section presents reduced-form evidence investigating the empirical relevance of both conditions.

3.1 External and internal consistency of survey answers

We conduct several tests to ensure that managers' survey responses reflect meaningful forecasts rather than trivial answers. We document that their answers are consistent with corresponding balance sheet data (external consistency) and that their answers to the different survey questions are related in theoretically expected ways (internal consistency).

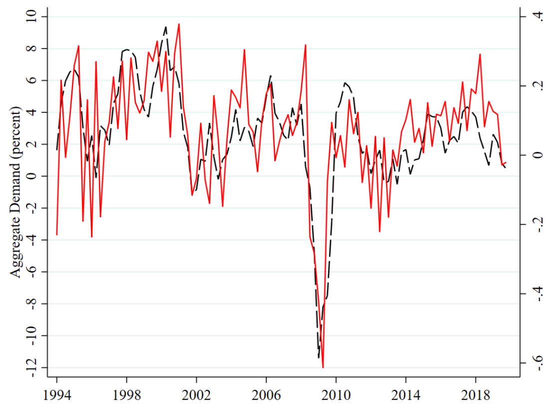
As a first step, Figure 3 illustrates the comovement between the year-on-year growth of aggregate demand for manufactured goods (based on national accounts) and the net balance of firms expecting an increase in their own demand versus those expecting a decrease. The strong correlation between the two series over the sample period suggests that the individual survey answers match quite well the actual aggregate dynamics. Appendix Figures A8, A9, and A10 further illustrate strong correlations between the survey responses and the corresponding actual aggregate variables (including production, demand, employment, prices, and wages).

[13] We exclude the period after 2019 to avoid dealing with the peculiar dynamics of the COVID-19 crisis.

[14] Appendix Table A2 provides more descriptive statistics for key firm characteristics and Appendix Table A3 presents additional descriptive statistics on the sectoral dimension.

These positive correlations emerge not only from firms' forecasts of their own outcomes, but also from their assessments of aggregate conditions, whether referring to past or anticipated outcomes.

Figure 3: Firms' Expected Demand vs. Actual Aggregate Demand



Note: The red line shows the difference between the fraction of firms in the survey who expect an increase in their demand over the next three months and the fraction of firms expecting a decrease in their demand. The black dotted line shows a measure of aggregate demand for manufacturing goods (consumption + exports + investment) from national accounts in France (y-o-y growth rate). We use y-o-y growth rate for actual aggregate demand to enhance data smoothness and mitigate residual seasonality effects, thereby facilitating clearer comparisons between actual and survey data.

We then compare managers' survey responses with corresponding administrative tax data for the same firm to assess reporting accuracy. Table 2 reports results of OLS regressions relating firm-level balance-sheet observations to answers of the quarterly survey. Column (1) relates firm's investment forecast for year t with what the same firm reports in the same survey as the realized value of investment for the same year. The correlation between the two variables is positive and large: when a firm forecasts an investment that is 1% higher than usual in calendar year t, its realized investment in the same year is also significantly higher than usual, by about 0.75%.

For a subperiod of our sample (2009-2019), we have information on the value of investment reported in firms' balance sheets. At the firm level, when we relate the value of investment observed in the administrative data to the realized and forecasted values reported by firms in the ECII survey, we find very strong correlations (Columns 2 and 3). Overall, managers report in the manufacturing survey information on investment values which are very close to those observed in firms' balance sheet data (Figure A11 illustrates the correlation between these different measures). Similarly, we find that firms reporting a larger forecast or realization of investment in the survey are also firms with a larger variation in their capital stock as observed in the balance-sheet data (Columns 4 and 5). Column (6) shows that firms reporting an increase in their workforce in the survey exhibit, on average, 2.9% higher observed employment growth in year t compared to when they report stable employment.

Table 2: External consistency of ECI and ECII survey responses

	$\log Inv^R_{i,t}$	$\log Inv_{i,t}$	$\log Inv_{i,t}$	$\Delta \log K_{i,t}$	$\Delta \log K_{i,t}$	$\Delta \log EMP_{i,t}$
$\log Inv^F_{i,t}$	0.754***	0.610***		0.032***		
	(59.19)	(35.10)		(10.19)		
$\log Inv^R_{i,t}$			0.689***		0.035***	
			(49.63)		(12.63)	
$EMP^R_{i,t}$						0.029***
						(9.77)
N obs	28 922	14 087	14 082	19 718	19 661	18 682
N firms	4 558	2 743	2 740	3 532	3 515	3 536
R^2	0.89	0.87	0.90	0.12	0.12	0.08

Note: Robust t-statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01. The dependent variables are $Inv_{i,t}$, the log realized investment for year t as reported in the FICUS–FARE balance-sheet dataset for 2009–2019; $Inv^F_{i,t}$, the log investment forecast for year t; and $Inv^R_{i,t}$, the log realized investment over year t as reported in the ECII survey. Both $Inv^F_{i,t}$ and $Inv^R_{i,t}$ are reported by the firm in the ECII survey. $Inv^F_{i,t}$ is computed as the average of the firm's quarterly responses about expected investment for calendar year t, while $Inv^R_{i,t}$ corresponds to the latest reported realized investment for year t. K_t is the stock of physical capital, as measured in the FICUS–FARE dataset. $EMP_{i,t}$ refers to the qualitative reported change in the number of employees in the ECI survey. $\Delta \log EMP_{i,t}$ is the change in employees between $t-1$ and t observed in FICUS–FARE. Sector*year and firm fixed effects are included.

Appendix Table A7 also provides evidence of internal consistency across different survey responses. It shows that firms expecting demand to increase are also more likely to anticipate increases in production, prices, and employment, while those forecasting a decrease in demand are less likely to expect increases in those outcomes.

This internal consistency reinforces the reliability of the survey data and suggests that firms form their expectations in a sensible manner, even if these expectations may contain systematic errors. Overall, both the external validation against administrative data and the internal consistency of survey responses provide strong evidence that firms' expectations reflect meaningful assessments of their business conditions.[15] This validation is crucial for our subsequent analysis of how expectation errors relate to resource allocation decisions.

3.2 Expectations of firm managers matter for their decisions

A key condition for expectation errors to contribute to misallocation is that firms' expectations play a significant role in shaping their decisions. Table 3 reports results of OLS regressions relating firms' expectations on their own demand with their decisions as measured in the balance-sheet data or in the investment survey. Our regressions also include firm fixed effects, sector*year fixed effects and some firm characteristics.

[15]In contrast, Bhandari et al. (2020) suggest a weaker correspondence between surveys of firm conditions and administrative data in the United States.

Table 3: Firms' own demand expectations and their economic decisions

	$\Delta \log PROD_{i,t}$	$\Delta \log EMP_{i,t}$	$\Delta \log WageBill_{i,t}$	$\log Inv^R_{i,t}$	$\log Inv_{i,t}$
$DMD^F_{i,t}$	0.038***	0.008***	0.009***	0.060***	0.073***
	(12.23)	(3.73)	(5.18)	(6.88)	(5.81)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N obs	22 298	22 356	22 338	29 342	15 338
N firms	3 913	3 924	3 923	4 633	2 957
R^2	0.10	0.07	0.09	0.82	0.85

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The dependent variables are variation between year $t-1$ and year$t$ of $PROD$, EMP and $WageBill$, the total production of a firm, its number of employees and the total wage bill paid to employees as measured in FICUS-FARE. $Inv^R_{i,t}$ is the amount of realized investment over year t, reported by the firm in the ECII survey, it corresponds to the last reported realized investment in year t. $Inv_{i,t}$ is the value of investment observed for year t in firms balance sheet data set (FICUS-FARE), this variable is available only for the period 2009-2019. $DMD^F_{i,t}$ is the forecast of a firm i about its own demand. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Column (1) shows a positive correlation between firms' qualitative expectations about their own demand and their realized production growth as reported in balance sheets. Columns (2) and (3) show a similar positive correlation between demand expectations and employment outcomes (either measured in terms of number of employees or in terms of total wage bill). Columns (4) and (5) show that firms' expectations about their own demand are also positively and significantly correlated with their realized investment (as measured from answers to the ECII survey or from the balance sheet data).

The link between expectations and decisions provides a channel through which expectation errors might contribute to misallocation in the economy. We examine this hypothesis directly in the next section by analysing the relationship between forecast errors and the dispersion in the marginal revenue products of capital and labor.

4 Forecast Errors and Misallocation

This section investigates whether heterogeneity in firms' demand forecast errors can be related to the dispersion in marginal revenue products of capital and labor. A key empirical challenge in linking forecast errors to misallocation is the possibility that a confounding factor may simultaneously influence both firms' expectations and their productivity. To address this, we progressively include several fixed effects and time-varying, firm-specific controls in our empirical setup. In particular, the long panel dimension of the survey and the large number of firms allow us to control for stringent fixed effects. Our baseline identification strategy compares firms with similar observable characteristics — such as size and age — within the same sector and year. We then reinforce this approach by conducting three complementary analyses. First, we show that the effect of forecast errors on marginal returns is highly persistent over time. Second, we include additional controls to better identify the specific role and contribution of demand forecast errors relative to other potential drivers of resource misallocation. Third, we examine the sources of forecast errors and show that part of these errors originates from firms' deviations from rational expectations, confirming that the resulting dispersion in marginal returns reflects inefficient allocation.

4.1 Baseline estimates

Our baseline empirical exercise consists of relating at the firm level MRPK and MRPL (observed in year t) to demand forecast errors (measured as the average forecast error on the firm's own demand in year t) using the following empirical set-up:

$$
\begin{aligned}
MRPK_{i,t} &= \alpha_i^K + \alpha_{st}^K + \beta^K DMD_{i,t}^{FE} + \Gamma^K Z_{i,t-1} + \varepsilon_{i,t}^K \\
MRPL_{i,t} &= \alpha_i^L + \alpha_{st}^L + \beta^L DMD_{i,t}^{FE} + \Gamma^L Z_{i,t-1} + \varepsilon_{i,t}^L
\end{aligned}
\tag{2}
$$

The dependent variable is the $MRPK_{i,t}$ or $MRPL_{i,t}$ of a firm i at time t as defined in Section 2.1. α_i are firm i fixed-effects capturing any time-invariant firm characteristics, α_{st} captures sector s (2-digit) by time t fixed-effects that control for sector-specific time-varying shocks, $DMD_{i,t}^{FE}$ measures the weighted expectation errors of firm i at time t as defined in Section 2.2, and $Z_{i,t-1}$ is a vector of time-varying firm controls. This vector includes the firm's age (in log) and its squared term (to capture potential non-linearities), firm size (measured as the logarithm of total assets) and its squared term, the number of products for which the firm reports demand expectations, and a dummy variable for dividend distribution (see Appendix A for details on the construction of these variables).

Panel A of Table 4 presents regressions results using MRPK as the dependent variable. Column (1) reports the simplest OLS regression without any fixed-effects or firm controls. We find that pessimistic firms (i.e., those with positive forecast errors, meaning they underpredict their own demand) are also the ones with higher MRPK. Quantitatively, a demand forecast error of $+1$ (e.g., firms expecting demand to decrease when it actually remains stable) is associated with a 9.1%-higher MRPK. The regression coefficient is statistically significant at 1%. This result is consistent with theoretical predictions: firms that are overly pessimistic about their own demand may underinvest, ending up smaller than their optimal size and with higher MRPK than other firms in the same sector if realized demand exceeds expectations.

To address potential confounding from industry-specific or macroeconomic factors, Column (2) introduces sector*year fixed-effects. These controls account for any sector-specific business cycles or technological changes that might simultaneously affect forecast accuracy and returns to capital. The coefficient remains stable at 0.08, suggesting that between-sector variation is not driving our results. By focusing on within-sector variation in MRPK, this specification also gets closer to the misallocation definition in the literature as the dispersion of MRPK within a sector.

Results presented in Column (3) includes firm fixed-effects alongside sector-year fixed effects, improving the identification by controlling for any unobserved firm characteristics explaining differences in MRPK. This specification exploits only within-firm time variation,

Table 4: Demand forecast errors and misallocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	-	2-digit	2-digit	2-digit	3-digit	4-digit	Between
				Panel A: $MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.091***	0.080***	0.053***	0.054***	0.050***	0.050***	0.069**
	(7.37)	(7.34)	(11.60)	(12.02)	(11.05)	(10.71)	(2.04)
Sector*Year FE		Yes	Yes	Yes	Yes	Yes	
Firm FE			Yes	Yes	Yes	Yes	
Firm controls				Yes	Yes	Yes	Yes
N obs	36 243	36 226	35 120	33 523	33 353	32 565	6 277
N firms	6 307	6 303	5 198	5 143	5 128	5 053	6 277
R^2	0.00	0.26	0.88	0.88	0.89	0.89	0.37
				Panel B: $MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.073***	0.073***	0.043***	0.041***	0.039***	0.039***	0.081***
	(15.46)	(15.72)	(13.71)	(13.49)	(12.48)	(12.20)	(6.39)
Sector*Year FE		Yes	Yes	Yes	Yes	Yes	
Firm FE			Yes	Yes	Yes	Yes	
Firm controls				Yes	Yes	Yes	Yes
N obs	36 583	36 565	35 428	33 648	33 477	32 693	6 339
N firms	6 395	6 391	5 256	5 180	5 165	5 090	6 339
R^2	0.01	0.11	0.64	0.66	0.66	0.67	0.32

Robust t-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. We report results from OLS regressions relating firm-level MRPK (upper panel) and MRPL (lower panel) to $DMD^{FE}_{i,t}$, the forecast error of firm i regarding its own demand, computed as the difference between the forecast made in t–1 and the realized value in t. The forecast error is initially measured at the product–quarter level and aggregated across products and years to obtain a firm–year measure. In each panel, the columns correspond to different specifications: Column (1) includes no controls or fixed effects; Column (2) adds sector–year fixed effects (at level 2 of the sector classification); Column (3) includes firm fixed effects; Column (4) adds other firm-level time-varying controls (age, squared age, size, squared size, number of products and dividend status); Columns (5) and (6) compute sector–year fixed effects using a more disaggregated sector definition; and Column (7) reports regressions using firm-level average values of the model variables, calculated over the period each firm is observed in the survey.

comparing a given firm at different points in time with different forecast accuracy. By controlling for time-invariant firm characteristics — such as managerial abilities, organizational structure, or persistent behavioral biases — this approach reduces concerns about omitted variable bias. The coefficient decreases to 0.053 but remains highly significant, indicating that when the same firm becomes more pessimistic about its demand relative to its average forecasting behavior, its MRPK increases.

Column (4) presents our baseline specification which further strengthens the identification of the estimated coefficient by including time-varying firm controls (such as firm size, age, and dividend distribution). These variables capture time-varying firm characteristics that might confound the relationship between forecast errors and misallocation. For instance, Chen et al. (2023) show that firms' sales forecast errors decrease with age. It is also well-known (Cloyne et al. 2023) that financial constraints tend to ease as firms age. Age could therefore influence both forecast errors and productivity, without necessarily implying a direct link between the two. Asriyan and Kohlhas (2025) also show that revenue forecast accuracy increases with firm size, which may also reflect the strength of financial constraints. Once we include these controls, our result remains robust: the estimated coefficient is positive and significant and the estimated coefficient is rather stable at 0.054.

To address concerns that our identification might be driven by overly broad industry classifications, Columns (5) and (6) use more granular fixed effects: specifically, 3-digit sector*year fixed effects in (5) and 4-digit sector*year fixed effects in (6). This ensures that we are comparing firms operating in very narrowly defined industries with nearly identical market conditions. The stability of the coefficients (0.050) in these two specifications confirms our baseline results.

Finally, Column (7) estimates Equation (2) but using the firm-level average of MRPK and forecast errors over the sample period. In that case, the identification will rely on cross sectional differences across firms within a given sector. The coefficient is again significant and positive, showing that firms on average more optimistic (resp. pessimistic) have a lower (resp. higher) MRPK. In Appendix, Figure A12 plots this (unconditional) positive relationship across firms.

Panel B of Table 4 reports results of the same specifications but using the firm-level MRPL as our dependent variable. We obtain very similar results across the different specifications. Our baseline specification in Column (4) shows that firms underestimating their demand by one unit have on average a 4.1%-higher MRPL than otherwise similar firms with accurate forecasts. The consistency of this effect across more conservative specifications in Columns (5) and (6) reinforces our interpretation.

In Appendix Table A8, we examine separately the effects of pessimistic versus optimistic demand forecast errors on firms' marginal revenue products. We do not find evidence of significant asymmetry in the response of MRPK or MRPL to demand forecast errors. Specifically, firms making pessimistic demand forecast errors have significantly higher MRPK and MRPL, whereas optimistic errors are associated with lower MRPK and MRPL. This highlights that both under- and overestimation of demand contribute to resource misallocation.

4.2 Robustness and heterogeneity

We run several additional exercises to test the robustness of our results to potential measurement issues. We then explore whether the effect of expectation errors differs across age and size of firms.

The literature on misallocation shows that the measure of MRPK can be biased when we rely solely on owned capital and when we ignore leased assets. In our estimations, if firms within the same sector use leasing differently to adjust their capital stock in response to shocks, our measure of MRPK will reflect this adjustment strategy rather than a true dispersion in marginal returns. We follow the usual practice in this literature and construct alternative measures of MRPK accounting for capital leasing (Eisfeldt and Rampini 2009).[16] First, we estimate the effect of forecast error on MRPK using total rental expenses of capital instead of tangible capital. Following Lim, Mann, and Mihov (2017) and Rampini (2019), we approximate a firm's leased capital in a given year as its total rental expenses multiplied by a factor of eight or ten (see Hu, Li, and Xu 2025, for a detailed discussion of this proxy). Results are reported in Appendix Table A9, which shows that we continue to find a positive and significant correlation between demand forecast errors and MRPK when using these alternative measures of MPRK.[17]

In Appendix Table A11, we report additional robustness results of our baseline regression relating MRPK or MRPL to demand forecast errors. We find that our main result holds when we do not remove MRPK or MRPL outliers from our estimation sample, when we consider only mono-product firms, when we measure demand forecast errors without weighting by the product shares and when we exclude small sectors. One potential concern is that firms may also increase their prices when expecting an increase in their demand, so that the demand does not increase ex post. This would generate a difference between expected and realized demand which could not be attributed to a forecast error. The last column of Table A11 reports regression results controlling for past price changes, as reported by firms, to address this concern. Our main result still holds.

We also estimate our baseline regression including the demand forecast error observed for each quarter of the year instead of the annual average forecast error (Appendix Table A15). We find that the demand forecast error has a positive and significant effect in all four quarters of the year. The forecast error in the fourth quarter of the year appears to matter less than that in the first three quarters, which is consistent with the intuition that forecast errors in the last quarter of the year have a smaller effect on MRPK within the same year.

To investigate how heterogeneous our results are across firms, we estimate our baseline model using quantile stratification by number of employees, total assets and firm age. Results are reported in Appendix Tables A12, A13 and A14. We find that the estimated coefficient associated with the demand forecast errors is positive and significant for all categories of firms. The effects are somewhat stronger for firms below the median size (in both employment and total assets), while remaining stable across age categories. Overall, forecast errors affect MRPK and MRPL similarly across firm types. Savignac et al. (2024) provide evidence that surveys in smaller firms are typically answered by the CEO, whereas in larger firms the task may be delegated to the CFO, for instance. Homogeneous results across firm sizes suggest that our findings are not driven by the position of the survey respondent within the firm.

[16] Leasing variables are available for the period 2001-2019 and we restrict our sample to this period for this robustness exercise.

[17] We also provide some robustness checks for the measurement of MRPL dividing the value added either by the total wage bill including social contributions or by the number of employees in Table A10, estimated parameters are significant, positive and close to the baseline case.

4.3 Dynamic effects

While our baseline results establish a contemporaneous relationship between forecast errors and misallocation, an important question is the extent to which these effects persist over time. Do forecast errors have long-lasting impacts on firm productivity, or do their effects dissipate quickly as firms adjust their factor inputs? To address this question, we estimate a series of local projections following the methodology of Jordà (2005). This approach allows us to track the dynamic response of MRPK and MRPL to demand forecast errors across multiple time horizons without imposing restrictive assumptions on the underlying dynamics. For each horizon h from 0 to 6 years, we estimate the following Equation (3):

$$\begin{aligned} MRPK_{i,t+h} &= \alpha_i^{k,h} + \alpha_{st}^{k,h} + \beta^{k,h} DMD_{i,t}^{FE} + \Gamma^{k,h} Z_{i,t-1} + \varepsilon_{i,t+h}^{k} \\ MRPL_{i,t+h} &= \alpha_i^{l,h} + \alpha_{st}^{l,h} + \beta^{l,h} DMD_{i,t}^{FE} + \Gamma^{l,h} Z_{i,t-1} + \varepsilon_{i,t+h}^{l} \end{aligned} \tag{3}$$

where $MRPK_{i,t+h}$ is the marginal revenue product of capital and $MRPL_{i,t+h}$ is the marginal revenue product of labor of firm i at time $t+h$, α_i^h denotes firm fixed-effects, α_{st}^h represents sector*time fixed-effects, $DMD_{i,t}^{FE}$ is the demand forecast error at time t, and $Z_{i,t-1}$ is our standard vector of time-varying firm controls. The coefficient of interest, β^h, captures the effect of a forecast error at time t on misallocation h periods ahead. By estimating separate regressions for each horizon, we allow all coefficients to vary flexibly across horizons.

Table 5: Local projections: Demand Forecast Errors and MRPK or MRPL at different horizons

	t	t+1	t+2	t+3	t+4	t+5	t+6
	Panel A: $MRPK_{i,t}$						
$DMD_{i,t}^{FE}$	0.054***	0.043***	0.024***	0.021***	0.022***	0.019**	0.007
	(12.02)	(8.14)	(3.88)	(3.09)	(2.66)	(2.52)	(0.87)
N obs	33 523	21 898	17 868	15 191	12 773	10 924	9 217
N firms	5 143	3 835	3 252	2 917	2 507	2 220	1 912
R^2	0.88	0.89	0.89	0.89	0.89	0.89	0.89
	Panel B: $MRPL_{i,t}$						
$DMD_{i,t}^{FE}$	0.041***	0.031***	0.018***	0.016***	0.010*	0.005	0.004
	(13.49)	(8.86)	(4.39)	(3.13)	(1.78)	(0.97)	(0.74)
N obs	33 648	22 073	18 020	15 302	12 877	10 992	9 242
N firms	5 180	3 878	3 287	2 945	2 537	2 236	1 915
R^2	0.66	0.66	0.66	0.65	0.66	0.66	0.66

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table reports results of local projection estimations relating firm-level MPRK (top panel) or MPRL (bottom panel) measured at different year horizons $t+h$ and the demand forecast error $DMD_{i,t}^{FE}$ measured at year t. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table 5 reports the dynamic response of MRPK (Panel A) and MRPL (Panel B) to demand forecast errors over a seven-year period. For MRPK, we observe that the effect of forecast errors is the strongest contemporaneously (0.054 at horizon 0) and decreases monotonically over time, becoming statistically insignificant by year 6. The effect remains economically meaningful for several years, with a one-unit increase in demand forecast error still associated with a 2.1% increase in MRPK three years later. This pattern suggests that while firms do adjust their capital stocks in response to realized forecast errors, the adjustment process is gradual and incomplete, leading to persistent misallocation. The dynamic response of MRPL follows a similar pattern. The effect of forecast errors on MRPL fades over time, ranging from 0.041 in the contemporaneous period to 0.016 three years later, becoming statistically insignificant by year 5. As robustness, in Appendix Table A16, we also include one lagged value of the demand forecast errors to control for potential persistence of the demand errors over time. The results are very similar: the maximum effects are obtained for horizons t but the effect of demand forecast errors in year t is also persistent and still significant at years $t+1$ to $t+4$ for both MRPK and MRPL.[18]

Overall, our results show that the relationship between forecast errors and marginal returns persists over a horizon of four to five years. This high persistence could reflect large adjustment costs. These costs imply that when firms adjust their inputs based on expectations that later turn out to be incorrect, it takes time for them to reverse those decisions and bring capital and labor back to optimal levels.[19] The persistence could also result from systematic forecasting biases. In both cases, such persistence implies that firms fail to reallocate resources efficiently even after new information becomes available. The persistent effects of forecast errors on misallocation highlight the importance of accurate expectations for efficient resource allocation. Our results suggest that forecasting errors can have long-lasting and inefficient effects on firm-level productivity. This finding has important implications for understanding business cycle dynamics, as it suggests that expectational shocks can have effects that persist well beyond their initial impact.

4.4 Alternative drivers of misallocation

While our analysis establishes a link between forecast errors and misallocation, the literature highlights several other potential drivers of resource misallocation. In this section, we complement our previous analysis by incorporating variables derived from firms' responses to the survey that capture these alternative drivers of misallocation. We show that the effect of demand forecast error on MRPK or MRPL persists even after controlling for these alternative drivers. We also assess how the contribution of the demand forecast error to the variance of MRPK and MRPL compares with the contribution of other potential drivers.

Theoretical and empirical literature has identified four main sources of misallocation: financial frictions, labor market rigidities, technological constraints and managerial abilities.

[18] We show in Appendix Table A16 that this pattern is not due to the attrition of firms over the estimation horizon: when we run the same regressions on the sample of firms for which MPRK and MPRL are non-missing during five consecutive years, the results are very similar.

[19] Bloom, Bond, and Van Reenen (2007) show that uncertainty reduces the responsiveness of investment to demand shocks, which may be explained by the significant costs of forecast errors. Zorn (2020) shows, using a model of investment with convex capital adjustment costs and rational inattention, that the interaction between these two frictions is key to understanding investment responses to shocks.

Financial frictions distort capital allocation when firms with high returns to capital are unable to obtain external financing, while firms with excess capital can access funds more easily (Rajan and Zingales 1998). Labor market frictions, such as hiring and firing costs or rigid employment regulations, can similarly distort firms' employment decisions (Hopenhayn and Rogerson 1993). Technological constraints, including adjustment costs and indivisibility in capital goods, can impede efficient resource allocation by preventing firms from operating at their optimal scale (Cooper and Haltiwanger 2006). Finally, managers differ in their ability to operate firms efficiently and their forecasting accuracy might reflect one dimension of this more general management ability (Bloom, Kawakubo, et al. 2021).

We extend our baseline regression by including proxies for alternative sources of misallocation to test whether the effect of demand forecast errors remains significant after controlling for these potential confounding factors. To do so, we leverage the detailed information contained in our three datasets to capture precisely each of these alternative drivers of misallocation. Appendix E provides a detailed description of the questions we use to construct our different survey-based variables.

We first complement the firm-level characteristics reported in balance sheets with self-reported indicators of financing difficulties.[20] In our firm surveys, firms report whether their production and/or their investment is limited by internal financing limits, borrowing constraints, and financing conditions. Second, we include measures of capital adjustment obstacles, including self-reported equipment, order-processing, and supply-chain bottlenecks. We also add a variable which captures technical factors limiting investment. This group of questions shed light on constraints that affect capital adjustments, such as installation costs, indivisibility, or time-to-build lags. Third, we consider measures of labor adjustment obstacles, such as self-reported workforce bottlenecks and hiring difficulties. Finally, we address the concern that unobserved managerial ability may drive both forecast accuracy and productivity by including measures of forecast accuracy on other outcomes than firm-specific demand. In particular, we include controls for forecast errors about aggregate outcomes such as production, prices and wages but also forecast errors about firm-level production, prices and employment — thereby isolating the specific role of demand forecast errors from a manager's general forecasting ability.[21]

Table 6 reports estimates from regressions in which we sequentially add the different sets of proxies for alternative drivers of misallocation. In Column (1), we report results of the baseline regression including firm and sector-year fixed effects and time-varying firm characteristics. We find that the point estimates associated with the demand forecast error are

[20] In our baseline specification, some proxies of financial constraints are already included because we control for firm age, size and dividend distribution which are standard proxies for these constraints used in the literature (see Ottonello and Winberry 2020 and Cloyne et al. 2023).

[21] Forecast errors about aggregate outcomes are constructed comparing the qualitative answer to the survey with the actual variation of the corresponding aggregate variable (producer price index for the manufacturing sector, industrial production index or base wage index for the manufacturing sector) as published by the French national statistical office.

Table 6: Controlling for alternative drivers of misallocation

	Demog.	+ Finan.	+ K adjus.	+ L adjus.	+ Manag. Fcasts		+ ProdCap.
					Firm	Agg.	
				Panel A: $MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.054***	0.050***	0.040***	0.039***	0.025***	0.025***	0.024***
	(12.02)	(10.85)	(8.66)	(8.56)	(4.05)	(4.09)	(3.76)
N Obs	33 523	24 851	24 851	24 851	23 110	22 276	22 212
N firms	5 143	4 210	4 210	4 210	4 016	3 902	3 898
R^2	0.88	0.89	0.89	0.89	0.90	0.90	0.90
				Panel B: $MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.041***	0.038***	0.031***	0.030***	0.017***	0.017***	0.016***
	(13.49)	(11.55)	(9.67)	(9.39)	(4.11)	(4.04)	(3.70)
N obs	33 648	24 883	24 883	24 883	23 137	22 325	22 260
N firms	5 180	4 221	4 221	4 221	4 024	3 915	3 911
R^2	0.66	0.67	0.67	0.67	0.67	0.68	0.68

Note: All regressions include firm and sector–year fixed effects. We report results from OLS regressions relating firm-level MRPK (upper panel) and MRPL (lower panel) to $DMD^{FE}_{i,t}$, the forecast error of firm i about its own demand, computed as described in Section 2. In each panel, columns correspond to different specifications: Column (1) includes sector*year and firm fixed effects and firm demographics (age, squared age, size, squared size, number of products and dividend status); Column (2) adds proxies for financial constraints (leverage and survey-based measures of financial constraints); Column (3) adds survey-based measures of capital adjustment constraints; Column (4) adds survey-based measures of labor adjustment constraints; Column (5) adds survey-based measures of managerial forecasting ability with measures of forecasting accuracy about their own firm-specific variables (production, employment, prices); Column (6) adds survey-based measures of managerial forecasting ability with measures of forecasting accuracy about aggregate variables (production, prices, wages); Column (7) adds survey-based measures of production capacity. Survey questions used to construct the survey-based measures are listed in Appendix Section E. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

positive and significant (0.054 for MRPK and 0.041 for MRPL). Column (2) reports results of a regression where we add balance-sheet variable (leverage) and survey-based indicators of financial constraints, our estimates remain quite the same. Columns (3) and (4) report results from regressions that include variables capturing obstacles to capital and labor adjustment. The effect of demand forecast errors remains significant. Columns (5) and (6) incorporate controls for accuracy of firms' expectations about their own outcomes and about aggregate variables. The coefficients associated with the demand forecast errors are somewhat lower than for the previous regressions but still positive and statistically significant. This test is the most conservative since forecast errors correlate across the different variables. Finally, Column (7) includes a direct production-capacity indicator, that would capture unobserved idiosyncratic shocks hitting the firm production. It slightly reduces the coefficients while preserving a positive and significant relationship between demand forecast errors and MRPK or MRPL.

Our results suggest that demand forecast errors are an additional and complementary driver of misallocation that operates alongside, but independently of financial/labor frictions, adjustment costs and observable differences in general ability of managers to make forecasts. Because some of these controls capture unobserved idiosyncratic shocks (such as variation in capacity utilization and reported bottlenecks) they help to rule out the possibility that the relationship is driven by confounding factors. This strengthens the connection between forecast errors and misallocation. Firms base their investment decisions on expected future demand; for a given level of financial or technological constraints, dispersion in forecast errors can be related to dispersion in marginal revenue products.

Table 7 reports the partial R^2 values associated with each set of explanatory variables considered above (Table 6) to assess how much each group of variables contributes to the dispersion in MRPK or MRPL.[22] The exercise proceeds by estimating firm-level regressions that include firm fixed effects and sector*year fixed effects, and then measuring how much additional variance is explained when each block of controls is added to the initial specification.

Our first finding is that each group of misallocation drivers accounts for only a modest share of the overall dispersion in MRPK or MRPL (between 0.27 and 4.72% of the variance of MRPK and between 0.39% and 5.61% of the variance of MRPL). This result is quite typical when working with granular firm-level data, as measurement error in the demand forecast but also in MRPK and MRPL will attenuate the R^2. Similarly, Gorodnichenko et al. (2025) report effects of comparable magnitude—between 0.4% and 1.3% from analogous factors in European and UK samples of firms. When we focus on relative partial R^2, we find that, consistent with the existing literature, financial constraints and firm demographics are the largest contributors to the explained dispersion of MRPK and MRPL, while demand forecast errors account for a smaller share (partial R^2 of 0.54% for MRPK and 0.77% for MRPL). This contribution of demand forecast errors is twice larger than the contribution of obstacles to labor adjustments, a third of the contribution of obstacles to capital adjustments and one-tenth of the contribution of financial constraints. This contribution of demand forecast errors is similar to that of the measures reflecting firms' forecasting abilities, both for their own outcomes and for aggregate variables. Our approach yields conservative estimates of the contribution of demand-forecast errors to MRPK dispersion for at least three reasons. First, the demand forecast error is measured as a qualitative variable, capturing only part of the true variation in forecast mistakes, which likely attenuates its estimated effect. Second, the survey gathers firms' forecasts over relatively short horizons, but forecast errors over longer horizons may have a larger impact on investment. Third, we identify the demand forecast-error channel using only a single variable, whereas we compare it to other broader categories that encompass many observables.[23]

We then compute a simple back-of-the-envelope TFP loss associated with each firm-level vector of misallocation drivers by converting the partial R^2 of each block of observables into a measure of aggregate productivity loss, following the approach of Hsieh and Klenow (2009). We provide details of our computations in Appendix G, following closely Gorodnichenko

[22] This approach follows Gorodnichenko et al. (2025) that uses variance decompositions and fixed-effect panel regressions to benchmark how much firm-level frictions contribute to productivity dispersion.

[23] When considering not only demand forecast errors but all forecast errors (for aggregate and firm-specific outcomes) that could directly or indirectly affect resource misallocation, the partial R^2 is 1% of MRPK and 1.25% for MRPL (see Appendix Table A17).

Table 7: Quantifying the relative contribution of various drivers of misallocation

	Partial R^2 (in %)		TFP loss
	MRPK	MRPL	(in %)
Demand forecast errors	**0.54**	**0.77**	**0.6**
Firm "demographics"	3.12	5.28	5.9
Financial constraints	4.72	5.61	5.5
Obstacles to capital adjustments	1.82	1.73	2.2
Obstacles to labor adjustments	0.27	0.43	0.3
Managers' forecasting ability:			
Firm outcomes	0.55	0.65	0.6
Aggregate outcomes	0.36	0.39	0.4
Production capacity	1.06	1.40	1.2

Note: Partial R^2 are obtained from firm-level regressions with firm and sector*year FE as described in Appendix Section F. The methodology for the computation of the TFP loss is described in Appendix Section G.

et al. (2025). We proceed in two steps. First, we interpret the residual dispersion in MRPK and MRPL (measured by the partial R^2) as reflecting inefficient input allocation across firms driven by the corresponding factor distortion. Second, under the small-variance log-linear approximation used in Hsieh and Klenow (2009), a given reduction in the variance of log marginal products corresponds to an approximate aggregate TFP gain that depends on input cost shares and the elasticity of substitution of output within sectors. This approach has been widely used in the literature and enables mapping marginal-return dispersion into aggregate output losses. We use standard values to calibrate the capital share ($= 0.33$), the labor share ($= 0.67$), and the elasticity of substitution ($= 3$).

The third column of Table 7 reports the TFP loss associated with each block of observables. Demand forecast errors translate into TFP loss of 0.6%. By contrast, the largest TFP losses are induced by financial constraints and frictions captured by firm demographics (5.5% and 5.9% respectively), whereas the lowest TFP losses arise from forecasting ability of managers and labor-adjustment frictions (around 0.3 and 0.6%). These numbers are presented as simple benchmarks rather than structural estimates. Focusing on the relative importance of the drivers of misallocation rather than on their absolute level, the TFP loss associated with demand forecast errors amounts to about 11% (0.6 vs. 5.5) of the TFP loss due to financial constraints, about one quarter (0.6 vs. 2.2) of the TFP loss from obstacles to capital adjustment, and about twice (0.6 vs. 0.3) the TFP loss from obstacles to labor adjustment.[24]

4.5 The predictable component of forecast errors

We have shown that forecast errors contribute to the dispersion in firms' MRPK and MRPL, and we have interpreted the persistence of this effect as indicating inefficiency in the resulting allocation. In this section, we present additional evidence that reinforces this interpretation.

[24]See Appendix Table A18 for TFP loss estimates with alternative assumptions. The level of TFP loss varies with these assumptions, but the relative magnitude between each driver is unchanged.

Specifically, we show that part of the observed forecast errors reflects deviations from rational expectations rather than idiosyncratic shocks. This finding strengthens our conclusion that the associated dispersion in firms' returns represents inefficient misallocation rather than an efficient response to firm-specific shock.

Under the full-information rational expectations (FIRE) assumption, forecast errors should not be predictable using information that was in the manager's information set at the time of the forecast. To test this deviation from FIRE, the usual tests consist of relating forecast errors at time $t+1$ to variables in the information set of the firm at time t. We run three of these standard tests. The first one examines whether firms systematically overreact to news about their own developments. The second test assesses the persistence of forecast errors by analyzing their autocorrelation. The third one shows that a non-negligible share of firms forecast errors can be predicted on average (see Appendix H for further details on the three tests). Appendix Table A19 provides evidence from the first two tests that strongly contradicts the FIRE hypothesis, in particular forecast errors is significantly correlated with new information, suggesting that firms overreact to news, while we also find a significant positive autocorrelation in forecast errors.[25]

Given that forecast errors influence firms' decisions (as shown in Section 3.2), these systematic deviations from the FIRE hypothesis may contribute to inefficient resource allocation. We therefore examine the extent to which dispersion in MRPK and MRPL is driven solely by predictable demand-forecast errors. To do that, we decompose the forecast error into predictable and unpredictable components. Formally, we estimate Equation (4) at the quarterly frequency, where Θ is a vector of variables in the information set of firm i for product p at time $t-1$. Θ includes the following variables in $t-1$: $DMD^F_{i,p,t-1}$, $PROD^F_{i,p,t-1}$, $EMP^F_{i,p,t-1}$, $DMD^R_{i,p,t-1}$, and backlog of orders. The fact that these variables are part of the firms' information set is important since it ensures that we are not relying on data accessible only to the econometrician, but on information that firms themselves actually observe. We use only a small subset of the variables in the firm's information set to show that our results are not an artifact of an overfitted model.

$$DMD^{FE}_{i,p,t} = \gamma + \lambda\,\Theta_{i,p,t-1} + \gamma_i + \epsilon_{i,p,t} \tag{4}$$

Consistent with our previous results, we find that λ is significantly different from 0. It provides additional evidence that firms make predictable expectation errors. Estimates are reported in Appendix Table A22. The R^2 of 31% suggests that, on average, about one-third of firms' forecast errors can be predicted using a small subset of information contained in their

[25]Our results are consistent with similar results found in different contexts (see Born, Enders, Menkhoff, et al. (2024) or Ma et al. (2024)). Appendix Table A20 also includes firm forecasts of aggregate variables and exhibits a pattern similar to that found in the literature (see Born, Enders, and Müller (2023) for a comprehensive survey of this literature) and Appendix Figure A13 shows the distribution of this overreaction parameter estimated using firm-by-firm regressions. In Appendix Table A21, we provide results of regressions where we estimate a dynamic panel GMM (Arrelano-Bover) allowing us to include firm fixed effects.

information set at the time of their forecast. In this first model, we implicitly assume that all firms have the same forecasting model (i.e. the same λ). We also estimate Equation (4) at the sector and firm levels (keeping firms with more than 20 quarterly observations). Appendix Figure A14 presents the distribution of R^2 resulting from the the sector-level and firm-level estimations.

To investigate the role of predictable versus unpredictable components of forecast errors in misallocation, we estimate the following Equation (5) using the fitted values (aggregated at the firm*year level) $DMD^{FE,Pred}_{i,t}$ as the predictable component of forecast errors and the residuals (also aggregated at the firm*year level) $DMD^{FE,Unpred}_{i,t}$ of Equation (4) as the unpredictable shock component of forecast errors:

$$\begin{aligned} MRPK_{i,t} &= \alpha^K_i + \alpha^K_{st} + \beta^{k,Pred}\, DMD^{FE,Pred}_{i,t} + \beta^{k,Unpred}\, DMD^{FE,Unpred}_{i,t} + \Gamma^K Z_{i,t-1} + \varepsilon^K_{i,t} \\ MRPL_{i,t} &= \alpha^L_i + \alpha^L_{st} + \beta^{l,Pred}\, DMD^{FE,Pred}_{i,t} + \beta^{l,Unpred}\, DMD^{FE,Unpred}_{i,t} + \Gamma^L Z_{i,t-1} + \varepsilon^L_{i,t} \end{aligned} \tag{5}$$

In Table 8, we report results where we estimate Equation (5) using the fitted values ($DMD^{FE}_{i,t}$ *Predictable*) and residuals ($DMD^{FE}_{i,t}$ *Unpredictable*) of Equation (4) using our three different forecasting models. We normalize the demand forecast error and its two components to a unit standard deviation to ease the comparison between estimated coefficients.[26] In Column (1) we find that one standard deviation increase in demand forecast errors is associated with a 0.031 standard-deviation increase in MRPK and a 0.056 standard-deviation increase in MRPL.

Columns (2)–(4) for MRPK and columns (6)–(8) for MRPL break down these effects into a predictable component and an idiosyncratic shock component, depending on the forecasting model. When using the forecasting model estimated on all firms pooled together, the coefficient on the predictable component is 0.012 for MRPK and 0.020 for MRPL, while the coefficient on the unpredictable component is 0.021 for MRPK and 0.042 for MRPL. This estimate should be seen as a lower bound, as the remaining unexplained errors may reflect a larger information set available to firms (compared to the econometrician's one) and limitations in our forecasting model. Using the sector-level and firm-level forecasting models yields very similar results. All coefficients are statistically significant at the 1% level, suggesting that both components contribute to misallocation.[27]

[26] In particular, we expect that the sum of coefficients associated to unpredictable and predictable forecast errors is equal to the coefficient associated with the overall forecast error (Column 1). The addition of fixed effects and control can however lead to some deviation between this sum and the coefficient estimated in Column (1).

[27] In Appendix Table A23, we provide estimates shown in Table 8 over a fixed sample of observations.

Table 8: Exploring the effect of the predictable component

	$MRPK_{i,t}$				$MRPL_{i,t}$			
	Baseline	Forecast model			Baseline	Forecast model		
		Pooled	Sector	Firm		Pooled	Sector	Firm
$DMD^{FE}_{i,t}$	0.031***				0.056***			
	(10.82)				(12.24)			
$DMD^{FE}_{i,t}$ *Predictable*		0.012***	0.010***	0.016***		0.020***	0.016***	0.021***
		(3.80)	(3.20)	(4.09)		(3.97)	(3.17)	(3.18)
$DMD^{FE}_{i,t}$ *Unpredictable*		0.021***	0.024***	0.016***		0.042***	0.046***	0.039***
		(7.57)	(9.32)	(5.21)		(9.54)	(11.56)	(8.03)
N obs	27 863	27 863	27 857	17 473	27 967	27 967	27 961	17 505
N firms	4 520	4 520	4 520	1 887	4 554	4 554	4 554	1 900
R^2	0.85	0.85	0.85	0.84	0.63	0.63	0.63	0.61

Note: Robust t-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Columns (1) and (5) reproduce the baseline result of Table 4 with the key variables normalized by their standard deviations. In Column (2) and (6), Equation (5) uses the fitted values ($DMD^{FE}_{i,t}$ *Predictable*) and residuals ($DMD^{FE}_{i,t}$ *Unpredictable*) of Equation (4) estimated over all firms pooled. In Column (3) and (7), $DMD^{FE}_{i,t}$ *Predictable* and $DMD^{FE}_{i,t}$ *Unpredictable* come from Equation (4) estimated for each sector. In Column (4) and (8), Equation (4) has been estimated for each firm (keeping only firms with at least 20 observations). Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

These findings show that misallocation driven by forecast errors is, at least in part, a result of deviations from full information rational expectations (FIRE). The significantly positive coefficients on the predictable components suggest that firms could potentially reduce misallocation by correcting for the systematic biases in their forecasting processes.

5 Inspecting the Mechanism

The intuition behind our main result is that when a firm anticipates higher future demand, it expects to expand production. Consequently, it invests more and hires additional workers to increase its production capacity. However, if actual demand falls short of expectations, the firm's optimism results in an excessively large capital stock and workforce relative to similar firms, leading to lower MRPK and MRPL.

To confirm this mechanism, we examine how firm-level demand forecast errors affect MRPK and MRPL through their impact on factor decisions. To do so, we follow a two-step approach. In a first step, we assess to which extent investment forecasts, realized investment or employment decisions in year $t-1$ can be explained by forecast errors *observed* in year t. The idea behind this first regression is to measure the share of investment or employment decisions taken in year $t-1$ that could be retrospectively attributed to a demand forecast error. Then, in a second step, we estimate whether these expected or realized investment and employment decisions which are retrospectively attributed to demand forecast errors are correlated with MRPK or MRPL. Table 9 reports the results of these two-step regressions.[28]

Columns (1) to (4) show that firms with demand forecasts that proved to be too pessimistic ex post (i.e. positive expectation errors in our case) report significantly lower investment forecasts (Column 1), lower realized investment – either using the survey answers (Column 2) or balance sheet data (Column 3) –, and lower realized employment compared to firms with accurate expectations (Column 4). These relations are statistically significant.

Table 9: Demand Forecast Errors, Investment and Employment Decisions

	Step 1: Production Factors				Step 2: Misallocation			
	$Inv^F_{i,t-1}$	$Inv^R_{i,t-1}$	$Inv_{i,t-1}$	$\Delta EMP_{i,t-1}$	$MRPK_{i,t}$	$MRPK_{i,t}$	$MRPK_{i,t}$	$MRPL_{i,t}$
$DMD^{FE}_{i,t}$	-0.051***	-0.064***	-0.076***	-0.012***				
	(-3.66)	(-4.13)	(-3.08)	(-3.60)				
Fitted $Inv^F_{i,t-1}$					-0.949***			
					(-8.66)			
Fitted $Inv^R_{i,t-1}$						-0.797***		
						(-9.08)		
Fitted $Inv_{i,t-1}$							-0.587***	
							(-6.01)	
Fitted $\Delta EMP_{i,t-1}$								-3.051***
								(-8.34)
N obs	19 920	20 128	9 851	15 701	19 477	19 680	9 649	15 349
N firms	3 571	3 595	2 189	2 979	3 495	3 521	2 148	2 924
R^2	0.87	0.83	0.85	0.06	0.89	0.89	0.92	0.68

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table reports results of a two-step regression approach. In the first step, we report results of regressions relating different investment measures (expected/realized as reported by firms in the ECII survey or observed in the firm balance sheet FICUS-FARE over the period 2009-2019) and employment variation (FICUS-FARE) on the ex-post demand forecast error $DMD^{FE}_{i,t}$. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included. For the second step, we report results of OLS regressions relating the value of investment and employment variation as predicted by the first step equation to the firm-level MRPK and MRPL (and including the same controls as in the first step).

Columns (5) to (8) show the results of estimations where we use the fitted values of investment or employment from the previous regressions (i.e. the value of investment and employment we attribute retrospectively to demand forecast errors) as regressors in our baseline equation relating MRPK and MRPL to forecast errors. The results indicate that lower fitted values - i.e., investment forecasts, investment decisions, or employment decisions based on overly pessimistic expectations — are associated with significantly higher marginal returns to capital and labor. This provides direct evidence in support of our mechanism: incorrect forecasts translate into distorted input decisions, which in turn affect firms' marginal returns to factors.

[28]This exercise is not an IV regression for which we would assume that demand forecast errors are an instrumental variable for investment or employment decisions. Our objective is to provide more insights on how forecast errors, investment and employment decisions and MRPK or MRPL are correlated.

Production capacity and inventories provide other channels through which forecast errors can lead to resource misallocation. When firms form overly optimistic expectations about future demand, they may increase their production capacity in anticipation of higher sales. If actual demand falls short, these firms are left with excess production capacity, production and then excess inventories. Conversely, firms that underestimate demand may invest and produce too little, leading to insufficient production capacity and use inventory to meet realized demand. Both scenarios reflect inefficient allocation of resources and contribute to dispersion in marginal returns.

To further investigate the role played by production capacity and inventories we examine how forecast errors affect MRPK through their effect on firms' self-reported production capacity constraints and inventories.[29] Table 10 presents results of our two-step empirical strategy presented above.

Table 10: Demand Forecast Errors, Production Capacity and Inventories

	Step 1		Step 2	
	$Q^{\text{ProdCap}}_{i,t}$	$Q^{\text{Invent}}_{i,t}$	$MRPK_{i,t}$	$MRPK_{i,t}$
$DMD^{FE}_{i,t}$	-0.047***	-0.084***		
	(-8.44)	(-11.69)		
Fitted Q^{ProdCap}			-1.150***	
			(-11.93)	
Fitted Q^{Invent}				-0.625***
				(-9.77)
N obs	33 790	21 832	32 911	21 213
N firms	5 201	3 707	5 076	3 613
R^2	0.37	0.27	0.88	0.88

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table reports results of a two-stage estimation approach. In the first stage, we report results of regressions relating firms' qualitative opinion on their production capacity or on their inventories on the demand forecast error $DMD^{FE}_{i,t}$. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included. In the second step, we report results of OLS regressions relating the capacity production or inventories (as predicted by the first step equation) to the firm-level MRPK and MRPL (and including the same control variables and fixed effects as in the first step).

Columns (1) and (2) of Table 10 confirm that forecast errors are on average related with firms' production capacity and inventory positions and that this relationship is significant. Column (1) shows that firms making pessimistic forecast errors about demand are more likely to report insufficient production capacity. Column (2) shows that the same firms are also more

[29] Q^{ProdCap} reports qualitative responses to the following ECI survey question: "*Given your current order book and the likely evolution of orders in the coming months, do you consider that your current production capacity is: more than sufficient (1), sufficient (0), or not sufficient? (-1)*", while Q^{Invent} reports qualitative responses to the question: "*Do you consider that, given the season, your current stocks of manufactured products are above normal (1), normal (0), or below normal (-1)?*".

likely to report inventories below normal levels suggesting that they may rely on existing stocks to compensate for inadequate production capacity.

Columns (3) and (4) present the results of the regression linking MRPK to the production capacity or the level of inventories predicted by the demand forecast errors. The results indicate that lower fitted values (i.e., insufficient production capacity and lower-than-normal inventory levels) are associated with significantly higher marginal returns to capital. This provides additional evidence in support of our proposed mechanism: incorrect forecasts lead to distorted input decisions, which in turn affect firms' marginal returns to factors.

Together, Tables 9 and 10 provide some empirical support for the proposed mechanism linking forecast errors to misallocation through investment decisions, capacity utilization and inventories. Firms form expectations about their future demand, invest accordingly to adjust their production capacity and inventories, and when these expectations prove inaccurate, they end up with either too much or too little capital relative to their actual needs. This directly impacts their marginal returns to capital and labor, creating the misallocation features that we document in our baseline results.

6 Conclusion

Firms are forward-looking by nature, and firms' managers must make important—and often hard-to-reverse—decisions today based on their expectations. However, this crucial aspect of firm behavior has received little attention in the literature. This is mainly due to the difficulty of quantifying managers' ability to think about the future and linking it to observable and measurable aspects of firm performance.

In this paper, by merging three high-quality datasets relating firm's expectation to their balance-sheet and financial statements, we are able to directly link these variables and show that a firm's ability to forecast its own development is key to understanding its performance. We further show that heterogeneity in firms' forecasting helps explain part of the dispersion in the marginal products of capital and labor observed in the data.

Using a rich dataset that combines French firm surveys with administrative records, we show that heterogeneity in firms' demand forecast errors contributes significantly to the dispersion in marginal revenue products of capital (MRPK) and labor (MRPL) within narrowly defined industries. Quantitatively, we find that a demand forecast error of $+1$ (i.e. demand under-prediction, for instance, firms expecting demand to decrease whereas it turns out stable) is associated with a higher MRPK by 5.4% and a higher MRPL by 4.1%. Leveraging the detailed survey data, we control for alternative drivers of misallocation and show that the expectation-errors channel operates above and beyond the usual drivers highlighted in the literature. We document the relative importance of this channel and show that its contribution to TFP losses is twice that of labor-adjustment frictions, and about 11% of that of financial constraints.

In addition, we provide evidence that the dispersion in MRPK and MRPL arising from forecast errors is inefficient. These errors are highly persistent over time, and firms fail to adjust their production structures even when new information becomes available. Moreover, we show that part of the forecast errors is predictable (31% in the most conservative specification), indicating a deviation from rational expectations and that this predictable component accounts for a non-negligible share of the MRPK and MRPL dispersions. Finally, we provide some evidence on the mechanism underlying our results. We show that when firms expect an increase in demand, they invest and hire more. When these expectations turn out to be wrong, they end up too large relative to their competitors, with lower MRPK and MRPL. Symmetrically, firms that underestimate future demand invest and hire too little, becoming too small and exhibiting higher MRPK and MRPL.

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APPENDIX

A Administrative Data (FICUS/FARE)

Table A1: Variable names and descriptions

Variable Name	**Description**
Age	Number of years since the date of establishment
Leverage	(Loans and similar debts + Other debts) / Total net assets.
Size	Total net assets
Dividend distribution status	Dummy Dividend > 0
Production	Total Production
Capital (K_t)	Tangible capital
Robustness 1 Capital	Net Tangible
Robustness 2 Capital	Tangible capital + 8*(Leased Capital)
Robustness 3 Capital	Tangible capital + 10*(Leased Capital)
Value-Added	Value-Added At Factor Cost
Robustness Value-Added	Gross Value-Added
Labor (L_t)	Total Compensation of Employees
Robustness Labor	Number of Employees
MRPK	$\log \frac{VA_t}{K_t}$
MRPL	$\log \frac{VA_t}{L_t}$

Note: MRPK and MRPL are trimmed at 1% at the top and bottom of the distribution. All variables come from tax records and are measured at year-end.

Table A2: Descriptive statistics

Variable	Mean	SD	p25	p50	p75
MRPK	-.29	.85	-.86	-.33	.23
MRPL	.6	.34	.42	.58	.78
Capital	62.8	315.6	2.8	10.1	36.9
Total Asset	119.6	659.7	5.4	17.3	56.2
Investment rate	3.4	20.3	0.4	2.9	6.7
Employment	375	1 156	56	138	327
Age	39	25	21	35	49

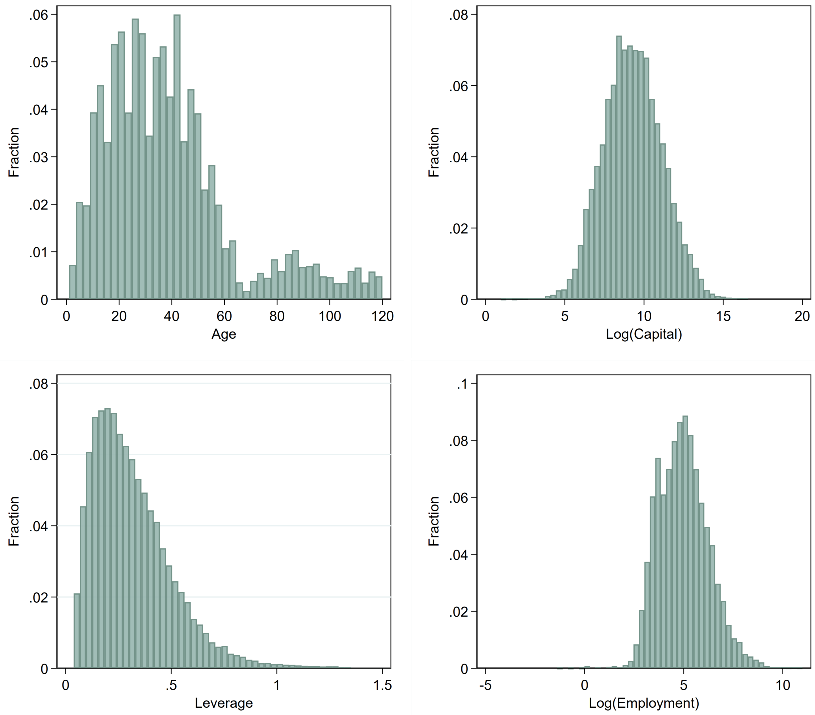
Note: MRPK and MRPL are measured as the logarithm of value added over tangible capital and as the logarithm of value added over total compensation of employees. Capital and total assets are expressed in million euros, employment in number of employees, age in years. The investment rate is calculated as the ratio between investment and capital (in %). Final dataset after merging ECI and FICUS/FARE data.

Table A3: Descriptive statistics on sector composition

Aggregation level	Number of sectors	Number of firms		
		Mean	SD	Max
2-digit	29	226.9	212.5	857
3-digit	98	67.8	67.2	358
4-digit	236	28.4	31.9	170

Note: the table reports the number of sectors in our sample at different levels of aggregations (column 1) and also statistics on the number of firms by sector for the different levels of sectoral aggregation considered (columns 2-5).

Figure A1: Distribution of various firm characteristics



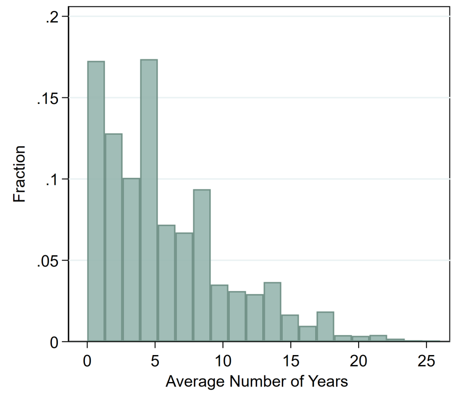
Note: This figure shows the distribution of firm age (upper left), firm size (upper right), firm leverage (bottom left) and firm investment rate (bottom right) in our sample. The distributions are obtained using variables from the balance sheet data set FICUS-FARE in our final sample.

Figure A2: Evolution of misallocation measures over time

Note: This figure shows the evolution over time of misallocation in capital and labor, measured as the weighted mean of the within-sector standard deviations of MRPK and MRPL, where the weights correspond to each sector's share of total value added.

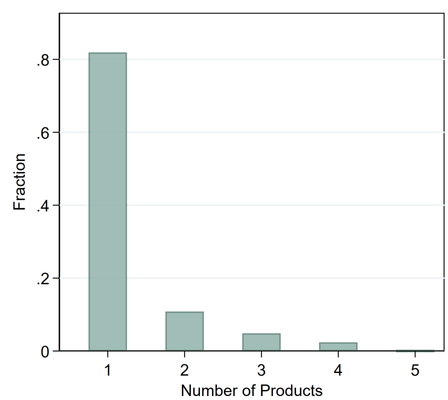
B Survey Data (ECI & ECII)

Figure A3: Number of years firms remain in the ECI survey



Note: This figure plots the distribution of the number of years during which firms report expectations and realizations of prices, demand and output.

Figure A4: Number of products by firm in the ECI survey



Note: This figure plots the distribution of the average number of products for which firms report expectations and realizations of prices, demand and output.

Figure A5: ECI Original

QUESTIONS RELATIVES AUX PRODUITS DE VOTRE ENTREPRISE	***(le cas échéant, mettre à jour la liste de produits pré-imprimés, SVP)***		
DESIGNATION DES PRODUITS *Veuillez cocher d'une croix la case qui convient ou entourer la flèche correspondant à votre réponse.* ***L'ensemble des questions posées ci-dessous concernent vos unités de production localisées en France :*** **Montant approximatif des ventes totales en 2018** *(hors taxes)*	.... milliers d'euros	.... milliers d'euros	.... milliers d'euros
1. VOTRE PRODUCTION			
a. Évolution au cours des 3 derniers mois	↗ ⇨ ↘	↗ ⇨ ↘	↗ ⇨ ↘
b. Évolution probable au cours des 3 prochains mois	↗ ⇨ ↘	↗ ⇨ ↘	↗ ⇨ ↘
2. LES COMMANDES (OU LA DEMANDE) GLOBALE(S) *(toutes provenances)*			
a. Évolution au cours des 3 derniers mois	↗ ⇨ ↘	↗ ⇨ ↘	↗ ⇨ ↘
b. Évolution probable au cours des 3 prochains mois	↗ ⇨ ↘	↗ ⇨ ↘	↗ ⇨ ↘
c. Sur la base des commandes enregistrées restant à exécuter et du rythme actuel de fabrication, pour combien de semaines estimez-vous que votre activité est assurée ?	environ ...... semaines	environ ...... semaines	environ ...... semaines
d. Considérez-vous que compte tenu de la saison, votre carnet de commande (ou votre demande) est actuellement	☐ supérieur(e) à la normale ☐ normal(e) ☐ inférieur(e) à la normale	☐ supérieur(e) à la normale ☐ normal(e) ☐ inférieur(e) à la normale	☐ supérieur(e) à la normale ☐ normal(e) ☐ inférieur(e) à la normale

Table A4: ECI English Translation

Questions	**Possible Answers**
1a. Evolution of your production over the last 3 months	Increase, Decrease, Unchanged
1b. Likely evolution of your production over the next 3 months	Increase, Decrease, Unchanged
2a. Evolution of orders (demand) over the last 3 months	Increase, Decrease, Unchanged
2b. Likely evolution of orders (demand) over the next 3 months	Increase, Decrease, Unchanged

Figure A6: ECII Original

A. Le montant annuel de vos investissements *(vous pouvez fournir des montants provisoires ou approximatifs)*

1 - Avez-vous réalisé des investissements en **2018** ?

OUI ☐ NON ☐ Si OUI, montant annuel de vos investissements 2018 (*)........................... .... milliers d'euros

2 - Avez-vous réalisé ou envisagez-vous de réaliser des investissements en **2019** ?

OUI ☐ NON ☐ Si OUI, montant annuel probable de vos investissements 2019 (*)............ milliers d'euros

3 - Envisagez-vous de réaliser des investissements en **2020** ?

OUI ☐ NON ☐ Si OUI, **montant annuel probable de vos investissements 2020 (*)** ...... milliers d'euros

(*) y. c. logiciels et investissements financés par crédit-bail.

Table A5: ECII

Questions	**Possible Answers**
1a. Did you make any investments in 20XX (current year)?	Yes, No
1b. If YES, annual amount of your investments in 20XX	.... thousands of euros
2a. Do you plan to make investments in 20XX? (next year)	Yes, No
2b. If YES, annual amount of your investments in 20XX	.... thousands of euros

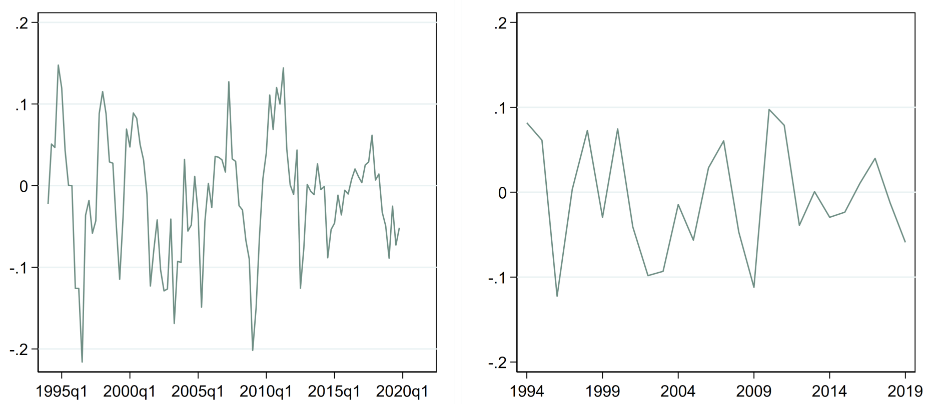
Every quarter, firms are asked about the investment they realized in years $t-1$ and $t-2$, as well as their planned investment for year t. As a result, each firm is asked up to eight times about its realized investment for a given year, and four times about its expected investment for that same year. We construct $Inv^R_{i,t}$ as the latest number reported for the realized investment in year t and $Inv^F_{i,t}$ as the average of the four reported forecasts, to be consistent with our construction of the yearly forecast in the ECI survey.

Table A6: Distribution of survey answers

(in %)	DMD^F	$PROD^F$	$PRICE^F$	EMP^F
Increase	20.3	23.1	17.3	10.9
Stable	58.4	55.9	72.9	73.3
Decrease	21.3	21.0	9.8	15.9
N obs	188 472	182 721	159 419	175 869

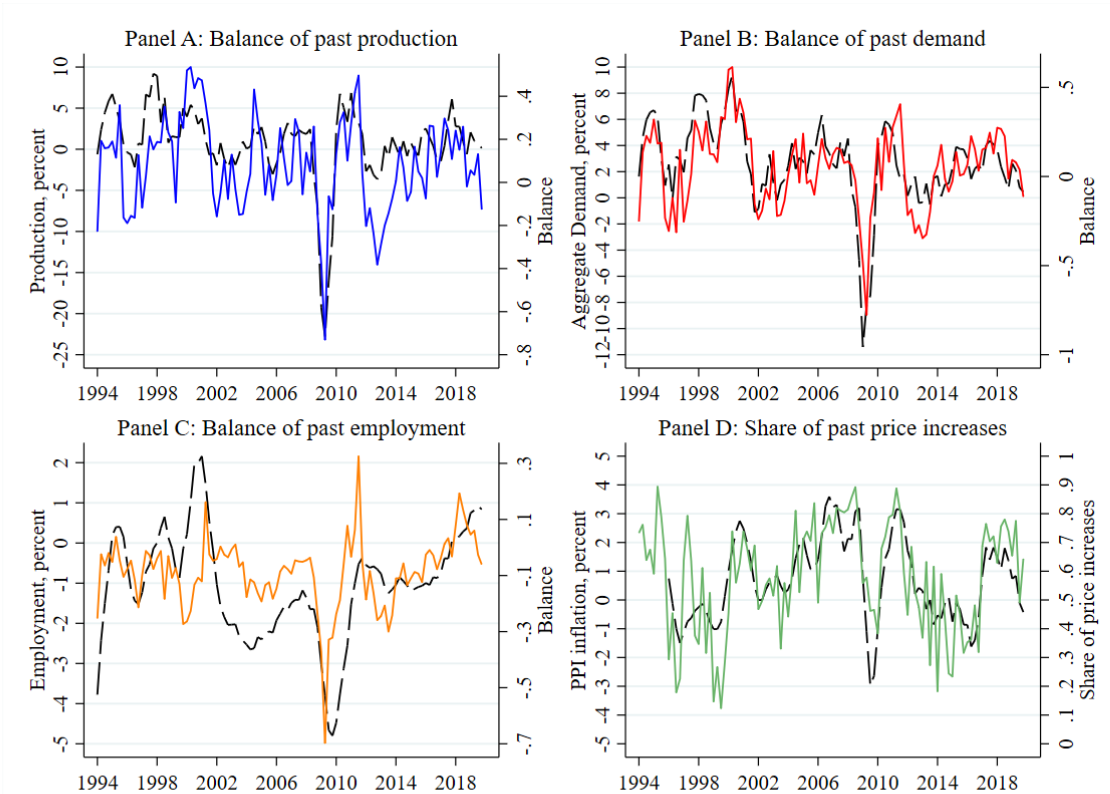
Note: Average proportion of qualitative categories reported by firms' managers when answering the different questions of the ECI survey. The questions cover their own prices and output and the demand addressed to their own products. Calculations have been made using the quarterly frequency data sets of answers over the period 1994Q1-2019Q4.

Figure A7: Evolution of forecast errors over time



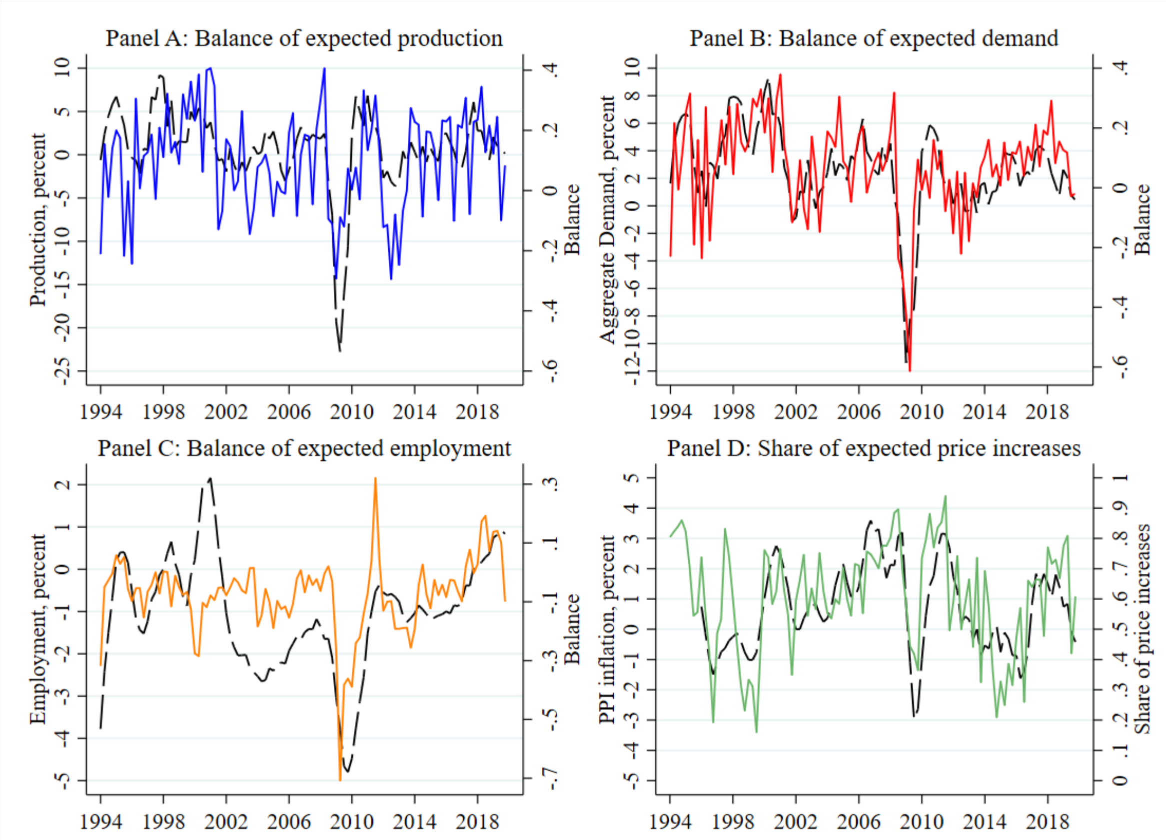
Note: This figure shows the variation of average firm demand forecast error per product*quarter (left panel) and firm*year (right panel).

Figure A8: Firms' Past Production, Demand, Employment and Price Changes vs. Actual Aggregate Production, Demand, Employment and Producer Price Changes



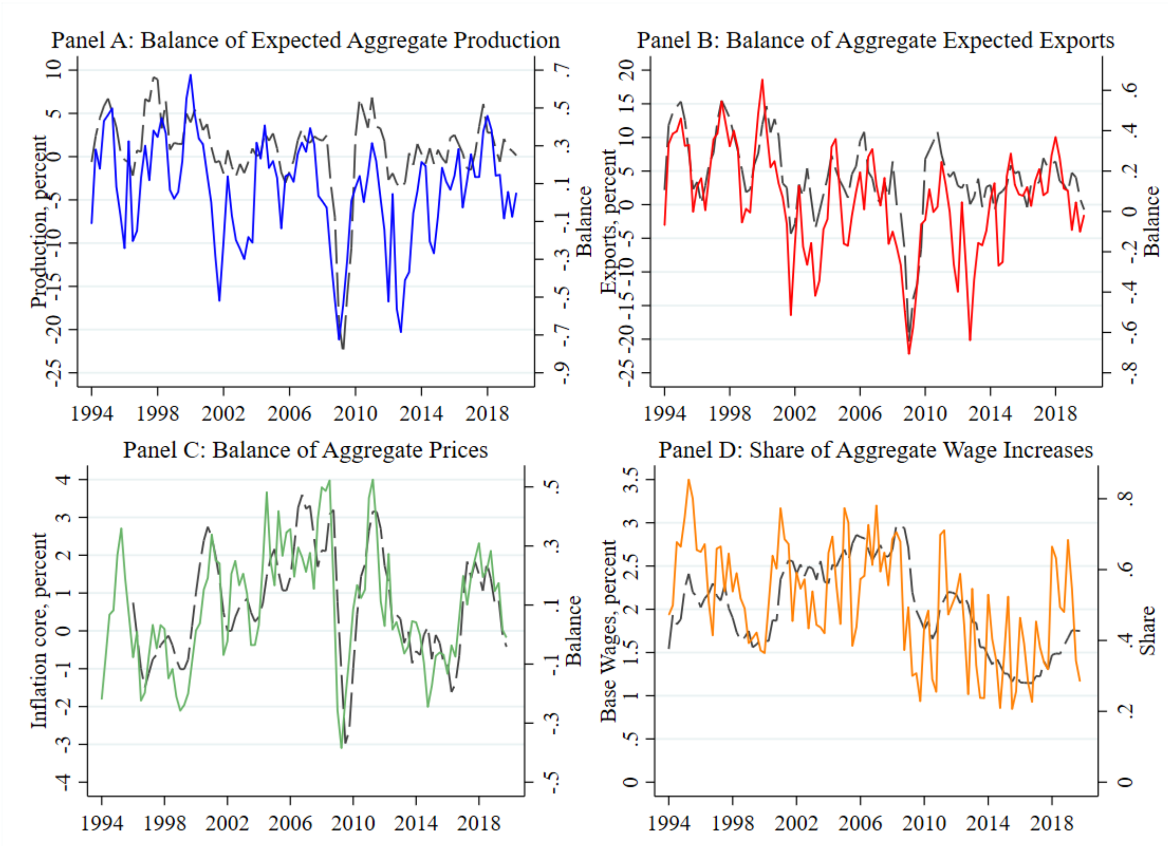
Notes: Panel A plots (in blue) the difference between the fraction of firms in the survey who report that they increased their production over the previous three months and the fraction of firms reporting a decrease as well as (in black) a seasonally adjusted measure of industrial production in France (y-o-y growth rate). Panel B plots the difference (in red) between the fraction of firms in the survey who report that their demand increased over the previous three months and (in black) the fraction of firms reporting a decrease i their demand as well as a measure of aggregate demand for manufacturing goods (consumption + exports + investment) from national accounts in France (y-o-y growth rate). Panel C plots (in orange) the difference between the fraction of firms in the survey who report that their employment increased over the previous three months and the fraction of firms reporting a decrease in their employment as well as (in black) a measure of employment in the manufacturing sector in France (y-o-y growth rate). Panel D plots (in green) the fraction of firms in the survey reporting a price increase over the last three months among price changes as well as (in black) a measure of producer price inflation in France (y-o-y growth rate, PPI excluding energy and food). We use y-o-y growth rate for actual aggregate variables to enhance data smoothness and mitigate residual seasonality effects, thereby facilitating clearer comparisons between actual data and survey data.

Figure A9: Firms' Expected Production, Demand, Employment and Price Changes vs. Actual Aggregate Production, Demand, Employment and Producer Price Changes



Notes: Panel A plots the difference between the fraction of firms in the survey who expect to increase their production over the next three months and the fraction of firms expecting a decrease as well as a seasonally adjusted measure of industrial production in France (y-o-y growth rate). Panel B plots the difference between the fraction of firms in the survey who expect an increase in their demand over the next three months and the fraction of firms expecting a decrease of their demand as well as a measure of aggregate demand for manufacturing goods (consumption + exports + investment) from national accounts in France (y-o-y growth rate). Panel C plots the difference between the fraction of firms in the survey who expect an increase of their employment over the next three months and the fraction of firms expecting a decrease in their employment as well as a measure of employment in the manufacturing sector in France (y-o-y growth rate). Panel D plots the fraction of firms in the survey expecting a price increase over the next three months among expected price changes as well as a measure of producer price inflation in France (y-o-y growth rate, PPI excluding energy and food).We use y-o-y growth rate for actual aggregate variables to enhance data smoothness and mitigate residual seasonality effects, thereby facilitating clearer comparisons between actual data and survey data.

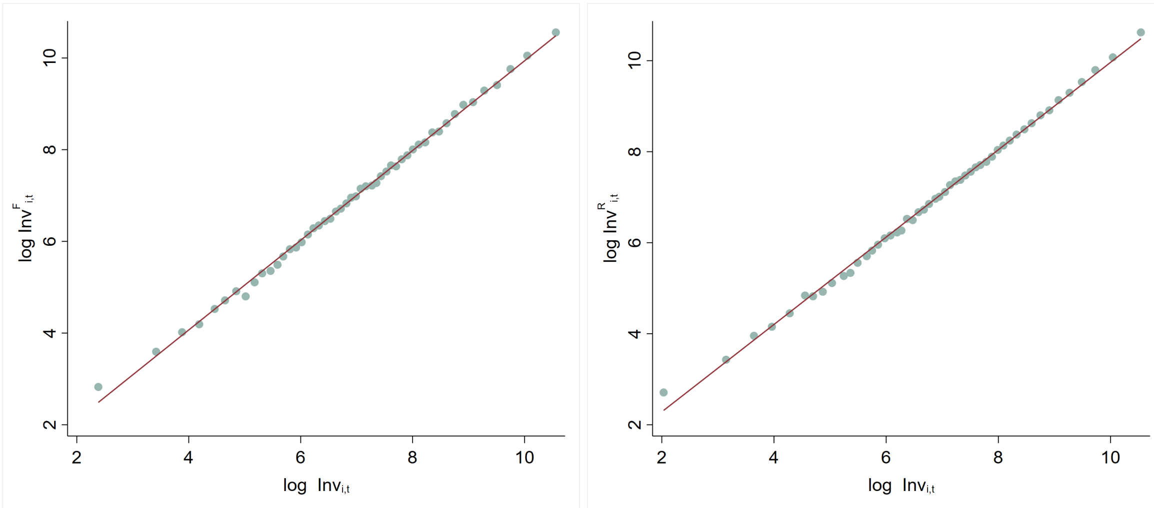
Figure A10: Firms' Expected Aggregate Production, Exports, Price and Wage Changes vs. Actual Aggregate Production, Export and Price and Wage Inflation



Notes: Panel A plots the difference between the fraction of firms in the survey who expect an increase of the aggregate production over the next three months and the fraction of firms expecting a decrease as well as a seasonally adjusted measure of industrial production in France (y-o-y growth rate). Panel B plots the difference between the fraction of firms in the survey who expect an increase of aggregate exports over the next three months and the fraction of firms expecting a decrease of aggregate exports as well as a measure of aggregate exports for manufacturing goods from national accounts in France (y-o-y growth rate). Panel C plots the fraction of firms in the survey expecting aggregate prices to increase over the next three months (among expected price changes) as well as a measure of producer price inflation in France (y-o-y growth rate, PPI excluding energy and food). Panel D plots the fraction of firms in the survey expecting aggregate wages to increase over the next three months (vs no change in wages) as well as a measure of base wage inflation in France (y-o-y growth rate). We use y-o-y growth rate for actual aggregate variables to enhance data smoothness and mitigate residual seasonality effects, thereby facilitating clearer comparisons between actual data and survey data.

C Survey consistency

Figure A11: External consistency of ECII survey responses



Note: This figure shows a binscatter of investment forecasts and realized investments as reported in the ECII survey, together with the corresponding investment measure from administrative data.

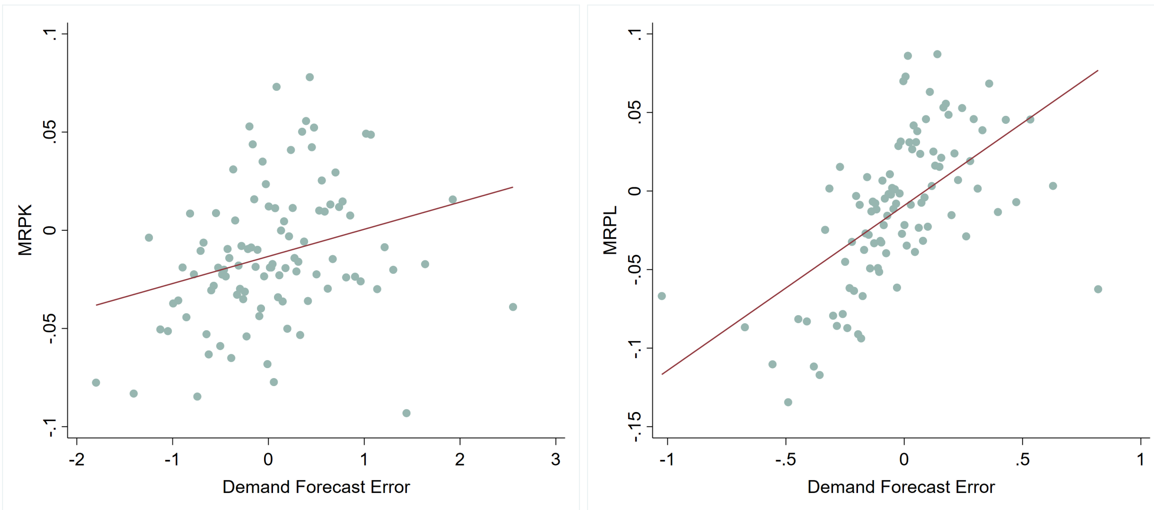
Table A7: Marginal effects on the probability to answer 'increase' to questions on the evolution of its own production, prices and employment

	$PROD^F_{i,t}$	$PRICE^F_{i,t}$	$EMP^F_{i,t}$
$DMD^F_{i,t}$ increase	0.650***	0.036***	0.104***
	(114.89)	(11.66)	(23.86)
$DMD^F_{i,t}$ decrease	-0.132***	-0.052***	-0.073***
	(-59.44)	(-19.46)	(-45.71)
N obs	182 330	158 822	175 178
Pseudo R^2	0.38	0.01	0.05

Note: This table reports marginal effects from an ordered Probit model where the dependent variables take 3 values ('increase', 'stable' and 'decrease'), marginal effects are calculated for the answer 'increase'. The exogenous variable is the qualitative answer to the question on expected demand addressed to the firm, it can take three values ('increase', 'stable' and 'decrease') (the category 'stable' is the reference category). When firms report that DMD^F increases, the probability to answer that production will increase is higher by 65 pp. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

D Forecast errors and misallocation

Figure A12: Forecast errors and misallocation between firms



Note: This figure shows the binscatter of the average demand forecast errors and the average MRPK or MRPL calculated at the firm level (averaging forecast errors, MRPK and MRPL over time).

Table A8: Asymmetric effect of demand forecast errors

	$MRPK_{i,t}$	$MRPL_{i,t}$
DMD^{FE} optimistic	-0.018***	-0.019***
	(-3.69)	(-5.79)
DMD^{FE} pessimistic	0.027***	0.017***
	(5.39)	(5.23)
N obs	33 523	33 648
N firms	5 143	5 180
R^2	0.85	0.62

Note: Robust *t*-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. This table reports results of OLS regressions relating the demand forecast error to MRPK and MRPL at the firm level. The forecast error is introduced in the regression as two dummy variables taking the value of 1 if the forecast error is classified as 'optimistic' (the realization is below the expectation) 0 otherwise and the other dummy variable 'pessimistic' corresponds to cases where the realization is above the expectation. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A9: Robustness across definitions of capital and MRPK

	(1) Baseline	(2) VA (excl. tax)	(3) Net Capital	(4) Leasing	(5) K+Leasing*8	(6) K+Leasing*10
$DMD_{i,t}^{FE}$	0.045***	0.045***	0.064***	0.049***	0.045***	0.045***
	(9.15)	(9.20)	(8.14)	(5.60)	(9.59)	(9.55)
N obs	23 441	23 461	23 356	23 912	23 731	23 737
N firms	3 970	3 969	3 956	4 043	4 019	4 019
R^2	0.90	0.90	0.83	0.80	0.85	0.84

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. This table reports OLS regressions relating the demand forecast error to the MRPK at the firm level, using different definitions of the two components of MRPK and with the key variables normalized by their standard deviations. Column (1) reports results of our baseline regression (including firm level controls, firm- and time-sector fixed effects), Column (2) reports results based on value added net of taxes, Column (3) reports results using capital net of depreciation, Column (4) reports results using leased capital measured as total rental expenses in a year, Column (5) reports results using total capital measured as capital in a year + total rental expenses in that year multiplied by a factor 8, Column (6) reports results using total capital measured as capital in a year + total rental expenses in that year multiplied by a factor 10. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A10: Robustness: Measurement of MRPL

	(1) Wage bill (Baseline)	(2) Wage bill incl. social contrib.	(3) Employment (No. of employees)
$DMD_{i,t}^{FE}$	0.041***	0.039***	0.049***
	(13.49)	(13.29)	(14.44)
N obs	33 648	33 218	33 690
N firms	5 180	5 139	5 187
R^2	0.66	0.62	0.81

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. This table reports OLS regressions relating the demand forecast error to the MRPL at the firm level, using different measures of MPRL. Column (1) reports results of our baseline regression where MRPL is measured as the log ratio between value added and wage bill (including firm level controls, firm- and time-sector fixed effects), Column (2) reports results where we also include social contributions paid by the firm to the total wage bill and Column (3) reports results where we compute MPRL as the ratio between value added and the number of employees within the firm on average in a given year. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A11: Robustness: MRPK or MPRL and demand forecast errors

	(1) Baseline	(2) Outlier	(3) Mono.	(4) Unw.	(5) SD	(6) Small	(7) Price
	Panel A: $MRPK_{i,t}$						
$DMD_{i,t}^{FE}$	0.054***	0.058***	0.056***	0.052***	0.028***	0.054***	0.050***
	(12.02)	(11.44)	(11.47)	(11.69)	(12.02)	(12.02)	(10.35)
N obs	33 523	33 908	28 176	33 523	33 523	33 523	27 641
N firms	5 143	5 187	4 485	5 143	5 143	5 143	4 592
R^2	0.88	0.87	0.88	0.88	0.88	0.88	0.88
	Panel B: $MRPL_{i,t}$						
$DMD_{i,t}^{FE}$	0.041***	0.047***	0.042***	0.039***	0.054***	0.041***	0.037***
	(13.49)	(12.20)	(12.91)	(13.20)	(13.49)	(13.49)	(11.31)
N obs	33 648	34 143	28 311	33 648	33 648	33 648	27 722
N firms	5 180	5 232	4 523	5 180	5 180	5 180	4 618
R^2	0.66	0.62	0.66	0.66	0.66	0.66	0.66

Note: Robust *t*-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Column (1) reports results of our baseline regression (including firm level controls, firm- and time-sector fixed effects), Column (2) reports results using the full sample of observation also including MRPK or MRPL outliers (defined as values below the 1st percentile and above the 99th percentile of the MRPK or MRPL distributions), Column (3) reports results restricting our sample to mono-product firms, Column (4) reports results where we use unweighted forecast errors, Column (5) reports results of a regression where both MRPK (or MPRL) and demand forecast errors are normalized by their standard deviation, Column (6) reports results of regression where we exclude small sectors, and Column (7) reports results of a regression controlling for past price variation as reported by the firm (to control for scenarios in which firms adjusted their price to counteract the increased forecasted demand, resulting in difference between realized and forecasted demand that is not due to forecast errors). Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A12: Demand forecast errors and MRPK or MRPL - By quartile of numbers of employees

	Baseline	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile
	Panel A: $MRPK_{i,t}$				
$DMD^{FE}_{i,t}$	0.054***	0.065***	0.058***	0.047***	0.038***
	(12.02)	(6.38)	(6.63)	(6.01)	(4.34)
N obs	33 523	8 081	8 139	8 134	8 287
N firms	5 143	1 454	1 539	1 512	1 316
R^2	0.88	0.89	0.90	0.91	0.88
	Panel B: $MRPL_{i,t}$				
$DMD^{FE}_{i,t}$	0.041***	0.043***	0.048***	0.034***	0.028***
	(13.49)	(7.57)	(8.70)	(5.77)	(4.08)
N obs	33 648	8 031	8 174	8 196	8 358
N firms	5 180	1 444	1 546	1 526	1 333
R^2	0.66	0.70	0.70	0.70	0.63

Note: Robust *t*-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Column (1) reports results of the baseline regression. Columns (2)–(5) report results for firms in the first, second, third, and fourth quartiles of the number-of-employees distribution, respectively. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A13: Demand forecast errors and MRPK or MRPL — By quartile of total assets

	Baseline	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile
	Panel A: $MRPK_{i,t}$				
$DMD^{FE}_{i,t}$	0.054***	0.054***	0.055***	0.044***	0.048***
	(12.02)	(5.65)	(6.30)	(5.52)	(5.14)
N obs	33 523	8 126	8 162	8 175	8 209
N firms	5 143	1 457	1 551	1 535	1 304
R^2	0.88	0.86	0.88	0.89	0.88
	Panel B: $MRPL_{i,t}$				
$DMD^{FE}_{i,t}$	0.041***	0.037***	0.048***	0.038***	0.032***
	(13.49)	(7.40)	(8.14)	(6.37)	(3.93)
N obs	33 648	8 193	8 232	8 208	8 161
N firms	5 180	1 475	1 570	1 544	1 301
R^2	0.66	0.63	0.67	0.68	0.63

Note: Robust *t*-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Column (1) reports baseline regressions. Columns (2)–(5) reports results of the same regression restricting the sample to the 1st–4th quartiles of the firm-size (total assets) distribution. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A14: Demand forecast errors and MRPK or MRPL — By firm age

	Baseline	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile
			Panel A: $MRPK_{i,t}$		
$DMD^{FE}_{i,t}$	0.054***	0.045***	0.049***	0.055***	0.044***
	(12.02)	(5.15)	(5.64)	(6.93)	(4.97)
N obs	33 523	8 057	8 439	8 247	7 795
N firms	5 143	1 703	1 767	1 666	1 355
R^2	0.88	0.91	0.91	0.90	0.89
			Panel B: $MRPL_{i,t}$		
$DMD^{FE}_{i,t}$	0.041***	0.036***	0.039***	0.038***	0.039***
	(13.49)	(5.87)	(6.75)	(6.74)	(6.15)
N obs	33 648	8 154	8 463	8 232	7 814
N firms	5 180	1 726	1 777	1 663	1 360
R^2	0.66	0.68	0.71	0.73	0.67

Note: Robust t-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Column (1) reports the baseline regression. Columns (2)–(5) reports results of the same regression restricting the sample to the 1st–4th quartiles of the firm-age distribution. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A15: Annual aggregation of DMD^{FE}

	$MRPK_{i,t}$		$MRPL_{i,t}$	
	Baseline	All	Baseline	All
$DMD^{FE}_{i,t}$	0.054***		0.041***	
	(12.02)		(13.49)	
$DMD^{FE}_{i,t}-1^{st}$ quarter		0.017***		0.011***
		(6.67)		(6.89)
$DMD^{FE}_{i,t}-2^{nd}$ quarter		0.013***		0.011***
		(5.49)		(6.71)
$DMD^{FE}_{i,t}-3^{rd}$ quarter		0.016***		0.012***
		(6.34)		(7.66)
$DMD^{FE}_{i,t}-4^{th}$ quarter		0.006**		0.005***
N obs	33 523	33 523	33 648	33 648
N firms	5 143	5 143	5 180	5 180
R^2	0.88	0.88	0.66	0.66

Note: Robust t-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Columns (1) and (3) report results of our baseline regression using the annual average forecast error, Columns (2) and (4) report results of the same regressions but including separately all the quarterly forecast errors. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.

Table A16: Local projections: robustness analysis

	t	t+1	t+2	t+3	t+4	t+5	t+6
Panel A: One lag of forecast errors as control							
				$MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.054***	0.046***	0.019***	0.020**	0.029***	0.023***	-0.001
	(9.90)	(7.29)	(2.64)	(2.34)	(2.89)	(2.69)	(-0.06)
N obs	22 114	15 210	12 346	10 248	8 615	7 373	6 228
N firms	3 864	2 906	2 437	2 100	1 811	1 587	1 400
R^2	0.89	0.90	0.90	0.89	0.89	0.89	0.89
				$MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.041***	0.035***	0.017***	0.017**	0.016**	0.007	0.003
	(10.66)	(7.92)	(3.27)	(2.55)	(2.22)	(1.08)	(0.36)
N obs	22 192	15 326	12 428	10 330	8 668	7 413	6 248
N firms	3 894	2 935	2 453	2 120	1 826	1 595	1 408
R^2	0.67	0.67	0.67	0.66	0.67	0.66	0.66
Panel B: Fixed sample of firms							
				$MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.047***	0.042***	0.036***	0.025***	0.018*	-0.002	-0.008
	(5.86)	(5.55)	(4.61)	(2.77)	(1.93)	(-0.23)	(-0.85)
N obs	7 464	7 464	7 464	7 464	7 464	5 340	4 190
N firms	1 554	1 554	1 554	1 554	1 554	1 141	912
R^2	0.91	0.92	0.91	0.91	0.90	0.91	0.91
				$MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.032***	0.029***	0.014***	0.014**	0.006	-0.013*	-0.005
	(6.32)	(5.46)	(2.61)	(2.22)	(1.00)	(-1.90)	(-0.74)
N obs	7 571	7 571	7 571	7 571	7 571	5 441	4 255
N firms	1 573	1 573	1 573	1 573	1 573	1 158	919
R^2	0.74	0.74	0.71	0.70	0.68	0.70	0.70

Note: Robust t-stats in parentheses clustered at the firm level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The table reports robustness results for local projection estimations relating firm-level MPRK or MPRL measured at different year horizons $t+h$ and the demand forecast error $DMD^{FE}_{i,t}$ measured at year t Our dependent variable of interest. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included. We report two types of robustness regressions: Panel A we restrict the sample to firms for which MRPK or MRPL is non-missing on a consecutive five year period of time (i.e. between year t and year $t+5$). Panel B we include one lag of the demand forecast error as a control in the regressions.

E Alternative drivers of misallocation

Financial constraints: Column (3) of Table 6 includes indicators based on:

- ECI question: *"Are you currently unable to expand your production as desired because of financial constraints?"*
- ECII question: *"Overall, the financing conditions for investment are a factor that is: very stimulating – stimulating – without influence – limiting – very limiting for your investment decisions?"*

Capital adjustment constraints: Column (4) of Table 6 includes indicators based on:

- ECI question: *"Are you currently unable to expand your production as desired because of insufficient equipment or machinery?"*
- ECI question: *"Are you currently unable to expand your production as desired because of insufficient demand?"*
- ECI question: *"Are you currently unable to expand your production as desired because of supply difficulties?"*
- ECII question: *"Overall, technical factors are a factor that is: very stimulating – stimulating – without influence – limiting – very limiting for your investment decisions? The technical factors considered here concern technological developments, including the constraints related to adapting the workforce to these new technologies"*

Labor market constraints: Column (5) of Table 6 includes indicators based on:

- ECI question: *"Are you currently unable to expand your production as desired because of a shortage of staff?"*
- ECI question: *"Are you currently experiencing difficulties in recruiting staff?"*

Capacity constraint: Column (7) of Table 6 includes indicator based on:

- ECI question: *"At what percentage of its available capacity is your firm currently operating?"*

F Partial R^2

We compute the partial R^2 associated with each vector of frictions by estimating Equation (6). We estimate this equation for each vector of frictions Θ^f based on a model with firm and sector*year fixed effects. The partial R^2 from these regressions indicates how much of the variance in MRPK or MRPL is due to each Θ^f. We follow the same procedure for MRPL and MRPK-MRPL (that will be used for computing the TFP loss associated with each vector of frictions).

$$MRPK_{i,t} = \omega_i^K + \omega_{st}^K + \mu^K \Theta_{i,t}^f + \varepsilon_{i,t}^K \tag{6}$$

$$MRPL_{i,t} = \omega_i^L + \omega_{st}^L + \mu^L \Theta_{i,t}^f + \varepsilon_{i,t}^L \tag{7}$$

$$MRPK_{i,t} - MRPL_{i,t} = \omega_i^{KL} + \omega_{st}^{KL} + \mu^{KL} \Theta_{i,t}^f + \varepsilon_{i,t}^{KL} \tag{8}$$

Θ^1 is a vector of firm characteristics (firm age, size, number of products, and dividend status), Θ^2 a vector of proxies for financial constraints composed of firms leverage and survey-based measures of financial constraints, Θ^3 a vector of survey-based measures of capital adjustment constraints, Θ^4 a vector of survey-based measures of labor adjustment constraints, Θ^5 a vector of survey-based measures of managerial skills, Θ^6 a vector of survey-based measures of production capacity constraint and DMD^{FE} the measure of demand forecast error described in Section 2. All survey-based variables are described in Sections 4 and E.

Table A17: Partial R^2 (in %) of forecast errors about firm-specific and aggregate variables

	MRPK	MRPL
Demand forecast errors	**0.54**	**0.77**
Firm forecast errors (demand + other outcomes)	0.68	0.87
Aggregate forecast errors + demand forecast error	0.87	1.12
All forecast errors	1.02	1.25

Note: Partial R^2 are obtained from firm-level regressions with firm and sector*year FE as described in Equations (6) and (7).

G Deriving productivity loss

We derive a formula for output and TFP losses when multiple frictions coexist in the economy. We follow Hsieh and Klenow (2009). For a full derivation, see Appendix A in Gorodnichenko et al. (2025). We provide in this appendix the intuition and the final expressions used for our computations.

Let τ_i^Y denote product-market distortions, and τ_i^K and τ_i^L input-market distortions. Let a and b be output elasticities of capital K_{it} and labor L_{it}, so that returns to scale are a+b. Let σ be the elasticity of substitution across varieties. Assume further that firm-level variables are log-normally distributed, and $a + b = 1$ (constant returns).

Following Hsieh and Klenow (2009) and Gorodnichenko et al. (2025), and assuming $\tau_i^K = 1$, the aggregate productivity loss can be approximated as:

$$\begin{aligned}\text{Loss} = &- \left(\frac{b(1-b)}{2} + \frac{b^2\sigma}{2}\right) [\text{Var}(\text{MRPK} - \text{MRPL})] \\ &- \frac{\sigma}{2}\text{Var}(\text{MRPK})\end{aligned} \tag{9}$$

Alternatively, assuming $\tau_i^L = 1$, the aggregate productivity loss can be approximated as:

$$\begin{aligned}\text{Loss} = &- \left(\frac{a(1-a)}{2} + \frac{a(1+a)\sigma}{2}\right) [\text{Var}(\text{MRPK} - \text{MRPL})] \\ &- \frac{\sigma}{2}\text{Var}(\text{MRPL})\end{aligned} \tag{10}$$

Equations (9) and (10) illustrate how dispersion in MRPK and MRPL translates into to aggregate productivity losses. Our objective is to decompose the total productivity loss into contributions from each type of friction. To do this, we isolate the effect of each friction vector by scaling the corresponding dispersion term in Equations (9) and (10) by the share of variance explained by Θ^f, i.e the partial R^2 associated with each vector of frictions Θ^f. We compute the partial R^2 as the simple difference (i.e., un-normalized) between the R^2 from a regression that includes the given friction f vector plus firm- and sector*year fixed effects and R^2 from a regression that only includes firm- and sector*year fixed effects. This metric therefore captures the proportion of within-firm variance in MRPK (or MRPL) that is explained by each type of friction taken separately.

The contribution of vector Θ^f to total TFP loss is obtained by scaling the total dispersion terms in Equation (9) by the corresponding partial R^2:

$$\text{Loss}^f = -\left(\frac{b(1-b)}{2} + \frac{b^2\sigma}{2}\right)\left[\text{Var}(\text{MRPK} - \text{MRPL}) \times \text{Partial } R^2_{kl,f}\right] - \frac{\sigma}{2}\text{Var}(\text{MRPK}) \times \text{Partial } R^2_{k,f} \tag{11}$$

For comparability, we set $b = 0.67$ and two distinct values of σ (3 and 5, the former being the value associated with our baseline calculations in the main text), as in Hsieh and Klenow (2009) and Gorodnichenko et al. (2025). Table A18 reproduces Table 7 with both TFP losses based on $\tau_i^K = 1$ and $\tau_i^L = 1$. The contribution of each friction relative to the others is comparable in all cases.

Table A18: Quantifying the relative contribution of various drivers of misallocation

	TFP loss (in %)			
	$\sigma = 3$		$\sigma = 5$	
	$\tau_i^K = 1$	$\tau_i^L = 1$	$\tau_i^K = 1$	$\tau_i^L = 1$
Demand forecast errors	**0.6**	**0.1**	**1.0**	**0.2**
Firm "demographics"	5.8	1.8	9.5	2.7
Financial constraints	5.5	1.1	9.2	1.8
Obstacles to capital adjustments	2.2	0.4	3.7	0.6
Obstacles to labor adjustments	0.3	0.1	0.5	0.1
Managers' forecast accuracy:				
Firm outcomes	0.6	0.1	1.1	0.2
Aggregate outcomes	0.4	0.1	0.7	0.1
Production capacity	1.2	0.3	2.0	0.4

Note: Partial R^2 are obtained from firm-level regressions with firm and sector*year FE as described in Appendix Section F. The methodology for the computation of the TFP loss is described in Appendix Section G. We compute TFP losses for two different values for the elasticity of substitution $\sigma = 3$ and $\sigma = 5$.

H FIRE deviations

We use forecast revisions as a measure of the news perceived by firms, capturing information about firm-specific developments in the spirit of Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015). At the firm level, this test analyzes deviations from rational expectations (see Born, Enders, Müller, and Niemann 2023). The second one is a test of persistence of forecast errors which consists of looking at the autocorrelation of errors.

Let $x_{p,t}$ be the realized value of x (e.g., demand, production, etc.) for product p at date t, and $F_{i,p,t-1}x_{p,t}$ be the forecast for x at horizon t made by firm i at time $t-1$ for product p. Then, $x_{t+1}^{FE} = x_{p,t+1} - F_{i,p,t}x_{p,t+1}$ is the forecast error of firm i for product p at date $t+1$ and $x_t^{FR} = F_{i,p,t}x_{p,t+1} - F_{i,p,t-1}x_{p,t}$ represents the forecast revision between $t-1$ and t. We estimate the following two Equations (12) and (13):

$$x_{t+1}^{FE} = \gamma + \lambda\, x_t^{FR} + \varepsilon_{i,p,t} \tag{12}$$

$$x_{t+1}^{FE} = \gamma + \lambda\, x_t^{FE} + \varepsilon_{i,p,t} \tag{13}$$

In both cases, under the FIRE assumption, λ should not be significantly different from zero, as forecasts should not be predictable using variables that are included in the firm's information set[30] — such as past forecast errors and forecast revisions.

Columns (1) to (3) of Appendix Table A19 present the results of the first test for three key variables: demand, production, and prices. The estimated coefficients are strongly negative and statistically significant across all specifications. These results indicate that firms systematically overreact to news. When firms revise their forecasts upward between $t-1$ and t — for example, when they initially anticipate a decrease in demand from $t-1$ to t but forecast an increase from t to $t+1$ — that is, when x_t^{FR} is positive, they tend to experience negative forecast errors thereafter, meaning that they were overly optimistic and overestimated the increase in demand.

Columns (4) to (6) of Table A19 present the results of a second test using the same variables of the survey. We test whether forecast errors are persistent over time, in other words, whether errors in the previous year can predict errors today. The coefficients are positive and statistically significant in all cases: 0.122 for demand forecast errors, 0.137 for production forecast errors, and 0.030 for price forecast errors. This indicates a significant positive autocorrelation in firms' forecast errors. One interpretation is that firms do not update their expectations after making errors, once again suggesting that they are not fully using the information available to improve their forecasts. We also estimate Equation (12) separately for each firm and present in Appendix Figure A13 the distribution of the resulting λ_i values.

[30] We are certain that the information revealed by firms in their survey responses is part of their information set.

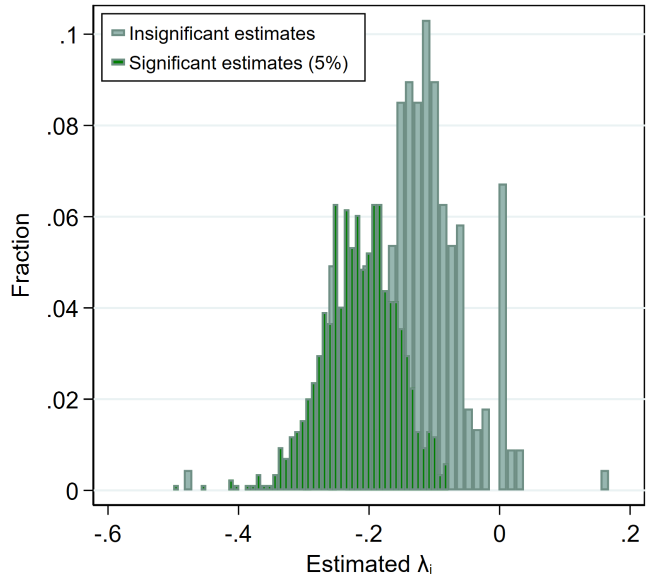
Table A19: Predicting firms' forecast errors

	$DMD^{FE}_{i,p,t+1}$	$PROD^{FE}_{i,p,t+1}$	$PRICE^{FE}_{i,p,t+1}$	$DMD^{FE}_{i,p,t+1}$	$PROD^{FE}_{i,p,t+1}$	$PRICE^{FE}_{i,p,t+1}$
Panel A: Forecast errors on forecast revisions regressions						
$DMD^{FR}_{i,p,t}$	-0.204***					
	(-132.48)					
$PROD^{FR}_{i,p,t}$		-0.193***				
		(-125.42)				
$PRICE^{FR}_{i,p,t}$			-0.180***			
			(-100.46)			
Panel B: Autocorrelation of forecast errors						
$DMD^{FE}_{i,p,t}$				0.122***		
				(27.36)		
$PROD^{FE}_{i,p,t}$					0.137***	
					(31.33)	
$PRICE^{FE}_{i,p,t}$						0.030***
						(5.55)
Sector*Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Prod FE	Yes	Yes	Yes	.	.	.
N obs	128 549	120 770	100 526	128 862	121 084	100 495
N firms	6 092	5 959	5 454	6 294	6 214	5 777
R^2	0.23	0.24	0.21	0.03	0.03	0.01

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Our dependent variables, $DMD^{FE}_{i,p,t+1}$, $PROD^{FE}_{i,p,t+1}$ and $PRICE^{FE}_{i,p,t+1}$ are the forecast error of a firm i for product p in a given quarter about its own firm demand, production and price, computed as the difference between a forecast made at date t (year-quarter) and the declared realization in $t+1$. $DMD^{FR}_{i,p,t}$, $PROD^{FR}_{i,p,t}$ and $PRICE^{FR}_{i,p,t}$ are the forecast revision of a firm i for product p about its own firm demand, production and price, computed as the difference between a forecast made in quarter $t-1$ and a forecast made in quarter t.

This overreaction pattern is robust across all variables we examine and, as shown in Appendix Table A20 holds even after controlling for firm-level forecast revisions in aggregate output and inflation. In Appendix Table A21, we provide results of regressions where we estimate a dynamic panel GMM (Arrelano-Bover), allowing us to include firm fixed effects. Results are similar, the autocorrelation is positive and significant, except for prices.

Figure A13: Distribution of estimated individual λ_i in Equation (12)



Note: This figure plots the distribution of λ_i coefficients estimated from Equation (12) at the firm level. This coefficient captures the elasticity of forecast errors to forecast revisions. Dark green bars plot the distribution of firm-level significant parameters, while the light green bars plots the statistically non-significant firm-level parameters.

Table A20: Aggregate forecasts in FIRE regressions

	$DMD^{FE}_{i,p,t+1}$	$PROD^{FE}_{i,p,t+1}$	$PRICE^{FE}_{i,p,t+1}$
$DMD^{FR}_{i,p,t}$	-0.204***		
	(-132.48)		
$PROD^{FR}_{i,p,t}$		-0.193***	
		(-125.42)	
$PRICE^{FR}_{i,p,t}$			-0.180***
			(-100.46)
$PROD^{AGG,FR}_{i,p,t}$	0.008***	0.007***	0.003**
	(5.10)	(4.34)	(2.27)
$PRICE^{AGG,FR}_{i,p,t}$	0.004***	0.003**	0.006***
	(2.57)	(2.01)	(4.00)
N obs	128 549	120 770	100 526
N firms	6 092	5 959	5 454
R^2	0.23	0.24	0.21

Note: Robust t-stats in parentheses clustered at the firm level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. This table presents the results of Equation (12) estimated on the full sample of firms and products. Forecast errors of different survey variables (defined at the firm i, product p level in a given quarter t) are related to forecast revisions of the same variable and also forecast revisions for aggregate qualitative variables (qualitative expectation on the aggregate production in the manufacturing sector and on the evolution of prices in the overall manufacturing sector). Sector*date (year-quarter) and firm*product fixed effects are included.

Table A21: Autocorrelation of firms' forecast errors

	$DMD^{FE}_{i,p,t+1}$	$PROD^{FE}_{i,p,t+1}$	$PRICE^{FE}_{i,p,t+1}$
$DMD^{FE}_{i,p,t}$	0.063***		
	(11.79)		
$PROD^{FE}_{i,p,t}$		0.076***	
		(14.09)	
$PRICE^{FE}_{i,p,t}$			-0.007
			(-1.14)
N obs	90 544	85 729	88 203
N firms	4 796	4 781	4 765

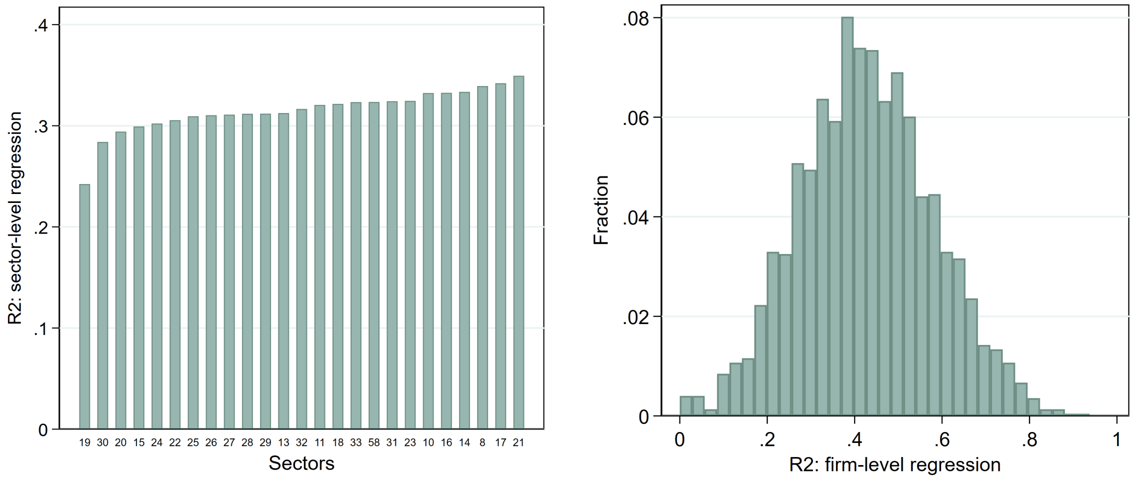
Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table presents results of a dynamic panel GMM estimations (Arrelano-Bover). We restrict the sample to firms answering more than 12 times to the quarterly survey. Our dependent variables, $DMD^{FE}_{i,p,t}$, $PROD^{FE}_{i,p,t}$ and $PRICE^{FE}_{i,p,t}$ are the forecast error of a firm i for product p about its own firm demand, production and price, computed as the difference between a forecast made date $t-1$ (quarter-year) and the declared realization in t.

Table A22: Estimating the predictable component of forecast errors

	$DMD^{FE}_{i,p,t}$	
$DMD^{F}_{i,p,t-1}$	0.387***	0.393***
	(140.18)	(138.81)
$PROD^{F}_{i,p,t-1}$	-0.060***	-0.061***
	(-23.34)	(-23.26)
Backlog order$_{i,p,t-1}$	-0.058***	-0.053***
	(-25.99)	(-22.06)
$DMD^{R}_{i,p,t-1}$	-0.105***	-0.074***
	(-49.38)	(-35.33)
$EMP^{F}_{i,p,t-1}$	-0.026***	-0.022***
	(-11.79)	(-9.08)
Firm FE	No	Yes
N obs	124 309	124 042
N firms	5 889	5 622
R^2	0.31	0.33

Note: Robust t-stats in parentheses clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. Our dependent variable, $DMD^{FE}_{i,p,t}$ is the forecast error of a firm i for product p about its own firm demand computed as the difference between the demand forecast made at date $t-1$ (quarter-year) and the declared realization at date t. We relate these quarterly demand forecast errors defined at the product-firm level to expectations made at date $t-1$ about demand ($DMD^{F}_{i,p,t-1}$), production ($PROD^{F}_{i,p,t-1}$), orders (Backlog order$_{i,p,t-1}$), employment ($EMP^{F}_{i,p,t-1}$) and realized demand at date $t-1$ ($DMD^{R}_{i,p,t-1}$).

Figure A14: R^2 of Equation (4) by sectors and by firms



Note: This figure shows the R^2 of Equation (4) estimated by firm (left panel) and by sector (right panel).

Table A23: Effect of predictable and idiosyncratic components

	$MRPK_{i,t}$				$MRPL_{i,t}$			
	Baseline	Forecast model			Baseline	Forecast model		
		Pooled	Sector	Firm		Pooled	Sector	Firm
$DMD_{i,t}^{FE}$	0.048***				0.039***			
	(8.39)				(9.52)			
$DMD_{i,t}^{FE}$ predict		0.036***	0.028***	0.033***		0.021***	0.015**	0.019***
		(3.29)	(2.61)	(4.09)		(2.78)	(1.98)	(3.18)
$DMD_{i,t}^{FE}$ shock		0.035***	0.044***	0.038***		0.035***	0.042***	0.040***
		(5.02)	(6.46)	(5.21)		(7.55)	(9.26)	(8.03)
N obs	17 473	17 473	17 472	17 473	17 505	17 505	17 504	17 505
N firms	1 887	1 887	1 887	1 887	1 900	1 900	1 900	1 900
R^2	0.84	0.84	0.84	0.84	0.61	0.61	0.61	0.61

Note: Robust t-statistics in parentheses, clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. We report results for the subsample of firms for which we are able to estimate the decomposition predictable vs unpredictable error and we also do not normalize the exogenous variables by their standard deviation. Sector*year and firm fixed effects and firm-level controls (age, squared age, size, squared size, number of products and dividend status) are included.