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 systematically deviate from rational expectations, resulting in 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.

Keywords: Heterogeneous firms, Capital misallocation, Forecast errors.
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1 Introduction

Resource misallocation, commonly measured by the dispersion in firms' marginal revenue products of capital (MRPK) and labor (MRPL), has been widely documented as key factor behind productivity differences across countries and over time. When firms operate at sub-optimal sizes – either too large or too small relative to their optimal productivity –, the impact on aggregate productivity and output can be substantial. Recent advances in firm-level survey data collection have renewed interest in the role of firms' expectations in driving investment and hiring decisions, which then shape the marginal returns to production factors. These surveys provide consistent evidence that firms' expectations deviate from the rational expectations hypothesis, which assumes that economic agents use all available information optimally when forming their forecasts. Instead, firms appear to rely on simplified heuristics or limited information, which may contribute to persistent resource misallocation and inefficiencies in production.

In this paper, using detailed firm-level data for French firms, we document that the observed dispersion in MRPK and MRPL across firms is related to heterogeneity in firms' forecasting accuracy. Specifically, we show that firms with less accurate expectations are more likely to make sub-optimal investment and hiring decisions, which in turn contributes to a greater misallocation of resources.

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 panel nature of the data provides a unique opportunity to study expectation formation processes over a long period of time. 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 firms' productivity with that of similar firms.

Before investigating how dispersion in MRPK and MRPL relates to forecast errors by firms' managers, we investigate three key necessary conditions for forecast errors to inefficiently influence the marginal revenue products of inputs. First, managers should provide sensible responses to the survey. Second, firms' expectations should matter for their decisions. Third, their expectations should deviate from the rational expectation benchmark, leading them to take suboptimal decisions. Our empirical findings confirm that these three necessary conditions are met by French 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. We second document reduced-form evidence showing that firms' expectations are significantly correlated with firms' investment and employment decisions. When firms expect an increase in their demand, their actual production and investment growth are higher compared to firms expecting stable demand. Similarly, firms expecting a decline in demand reduce their employment relative to firms expecting stable demand. Third, we document that firms' expectations about their own business conditions are not consistent with rational expectations. Specifically, we find that firms tend to overreact to news, as evidenced by a negative correlation between forecast revisions and subsequent forecast errors. This pattern is robust across multiple variables, including demand, production, and prices. We also document that forecast errors are auto-correlated. These two results contradict the key implication of rational expectations that forecast errors should be unpredictable.

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. Our result also holds once we control for other usual drivers of misallocation such as financial and labor market constraints. Besides, the effects are robust across increasingly fine-grained industry classifications, comparing firms within narrowly defined 4-digit sectors facing almost identical market conditions.

To understand the relative importance of different types of forecast errors, we decompose them into predictable components - systematic deviations from rational expectations - and unpredictable components, which reflect shocks or errors that cannot be predicted based on the available information set. Both components contribute significantly to misallocation. This suggests that firms could improve their resource allocation by addressing systematic biases in their forecasting processes.

Using a survey of the exact same firms about their investment outlook, the *Enquête de Conjoncture sur les Investissements dans l'Industrie* (ECII), we are also able to document one possible channel through which expectations errors might affect MRPK and MRPL. When firms expect an increase in their demand, they invest more 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. We provide direct evidence that ex post forecast errors are correlated with firms' investment and hiring decisions. Moreover, 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. In other words, increasing inputs based on what are revealed ex post to be forecast errors lower a firm's marginal revenue product of inputs relative to otherwise similar firms.

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 financial frictions (Buera and Shin 2013, Hopenhayn 2014, Midrigan and Xu 2014, Karabarbounis and Macnamara 2021, Su 2024, among others) and labor market frictions (Bilal et al. 2022, Alpysbayeva and Vanormelingen 2022, Heise and Porzio 2022, among others). Other strands of research emphasize the role of adjustment costs and idiosyncratic shocks (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) and institutional and policy environments (Bartelsman, Haltiwanger, and Scarpetta 2013, Gorodnichenko et al. 2025, among others). This paper contributes to this investigation of the sources of misallocation by showing that non-rational 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 and Venkateswaran (2019) and David, Hopenhayn, and Venkateswaran (2016) 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) affects the dispersion of realized returns. In contrast, we observe firms' expectations of their own conditions and provide direct evidence 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 studies 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 and interact with real frictions, leading to important and 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 three fundamental stylized facts about expectation formation, which are key for understanding how forecast errors can influence MRPK and MPRL: managers' expectations are meaningful, firms' decisions respond to their expectations and firms' expectations deviate from the rational expectations benchmark. Section 4 analyzes how forecast errors correlate with observed MRPK and MRPL. Section 5 provides some supporting evidence for the mechanism at work. Section 6 concludes.

2 Data and Measurement

In this paper, we relate, at the firm level, the marginal revenue products of capital and labor (MRPK and MRPL) to the forecast error of firms on the demand addressed to them. To do so, we combine two high-quality firm-level data sets: a balance-sheet data set covering the universe of French firms to measure the MRPK and MRPL and a large survey data set collecting expectations and outcomes of several variables as reported by business leaders of manufacturing firms to measure their forecast errors.[2] This section presents these data sets and how we compute our main variables of interest from these data sources.

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 tangible capital ($\log \frac{VA_t}{K_t}$) and firms' MRPL as the logarithm of value added over total compensation of employees ($\log \frac{VA_t}{W_t}$). Following standard practice in the literature (Hsieh and Klenow 2009, Bau and Matray 2023 or Albrizio,

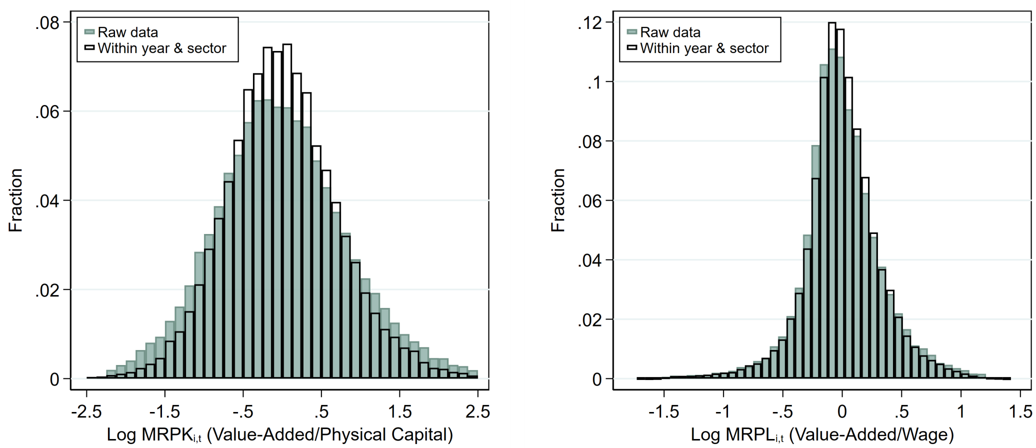
[1]This literature builds on works showing the key role of information issues in macroeconomic dynamics (Angeletos and Lian 2016, Angeletos, Huo, and Sastry 2021) and data-driven decision making in firm performance (Brynjolfsson and McElheran 2016).

[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*.

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.[3]

The data for these calculations come from FICUS and FARE, two comprehensive administrative databases derived 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 distribution of MRPK (left panel) and MRPL (right panel), using raw data (green bars) and MRPK/L net of year and sector fixed effects (transparent 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, while the darker outlined 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.[4]

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 that a firm at the 75^{th} percentile of the distribution has a marginal revenue product of capital

[3]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 that exploits how revenue growth responds to input growth within firms across plants (see Bils, Klenow, and Ruane 2021).

[4]Appendix Figure A2 plots the evolution over time of the average standard deviation of MRPK/L across sectors.

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 in comparable circumstances.[5]

This observed dispersion in marginal returns could stem from various sources, including financial frictions, adjustment costs, or regulatory constraints. A key question we explore in subsequent sections is whether heterogeneity in firms' forecast errors contributes to this observed misallocation.

2.2 Forecast errors

We derive firms' expectations and 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. 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 all firms with more than 20 employees of 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.[6] We present in Appendix Figure A3 the distribution of the number of years firms are observed in these surveys. This longitudinal dimension is critical for separating systematic, firm-specific biases from temporary forecast errors, which allows for a more precise identification of their impact.

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

[5]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 (listed firms, across all sectors). They found similar results on the dispersion of MRPK and MRPL with their sample of French firms as the one documented using our sample (1 pp for standard deviation of MPRK and 0.5 pp for standard deviation of MRPL).

[6]See Andrade et al. (2022) for an extensive description of this survey.

on aggregate production, prices, or wages. Some questions like prices, demand or production are asked for the different main products of the firm.[7] 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).[8] 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.[9]

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'.[10]

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 realized 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: 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.

Table 1 outlines our classification of these errors. A firm is labeled as 'strongly over-predicting' a variable if it anticipated an increase but the realized outcome was a decrease

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

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

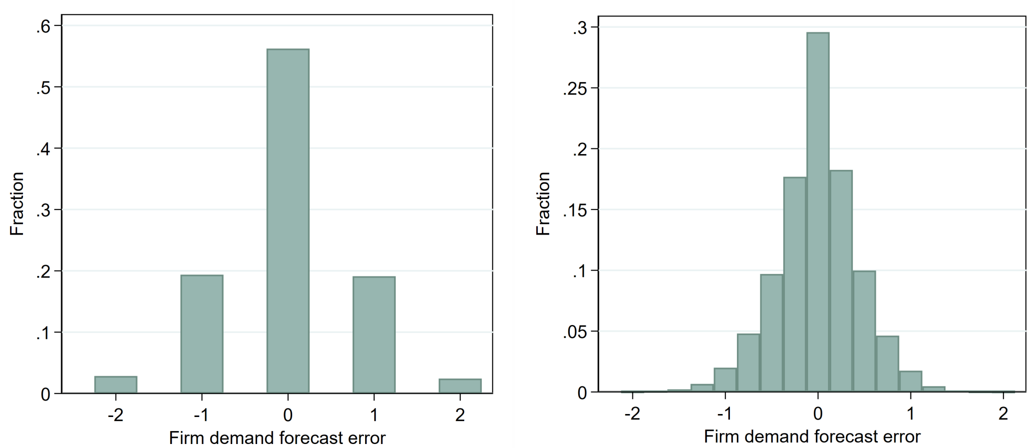
[9]We present in Appendix Figures A5 and A6 the original questions asked in ECI and ECII surveys. Tables A2 and A3 provide the English translation of these questions.

[10]Appendix Table A4 presents the distribution of answers for the main variables.

($x^{FE}_{i,p,t} = -2$). Symmetrically, a firm is labeled as 'strongly underpredicting' if it anticipated a decrease but the outcome was an increase ($x^{FE}_{i,p,t} = 2$). Less extreme errors include 'underpredicting' ($x^{FE}_{i,p,t} = 1$) and 'overpredicting' ($x^{FE}_{i,p,t} = -1$), while forecasts with no error are considered 'accurate' ($x^{FE}_{i,p,t} = 0$).

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 displays by construction a more continuous distribution than the product*quarter level distribution.

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 measure 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.

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

Once we matched firm-level data sets containing MRPK and MRPL and survey data containing the forecast errors, our final sample contains 36 312 observations from 6 307 unique firms spanning 1994 to 2019.[12] 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.[13] The merged dataset 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.

3 Stylised Facts on Firms' Expectation Formation

In theory, expectations errors of firms' managers will be related to misallocation (i.e. the inefficient dispersion of MRPK and MRPL) if three necessary conditions are fulfilled: (1) managers provide meaningful answers to the survey and not trivial answers; (2) their expectations on their own variables matter for their economic decisions; (3) their expectations are not aligned with the full-information rational expectation hypothesis. This section presents reduced-form evidence investigating the empirical relevance of these three conditions.

3.1 External and internal consistency of survey answers

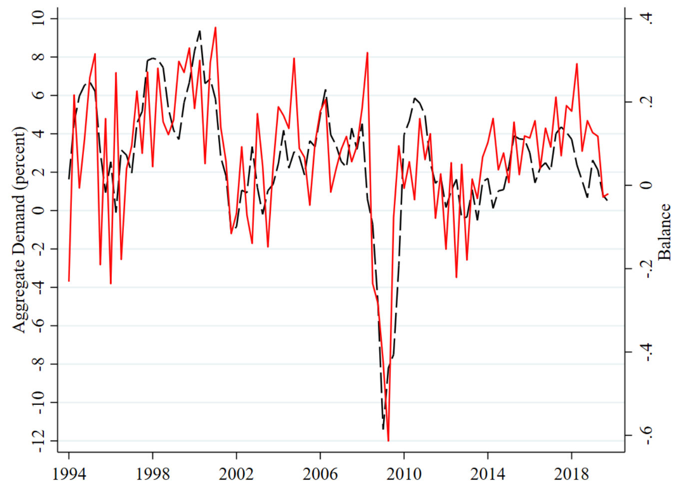
We conduct several tests to ensure that managers' survey responses reflect meaningful forecasts rather than trivial answers. We document that their answers are consistent with corresponding balance sheet data (external consistency) and that their answers to the different survey questions are related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

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

[12]We exclude the period after 2019 to avoid dealing with the peculiar dynamics of the COVID-19 crisis.
[13]Appendix Table A5 provides more descriptive statistics for key firm characteristics
[14]Appendix Table A6 presents additional descriptive statistics on this dimension.

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: This figure 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). 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 1%-larger investment in calendar year t, the realized investment for the same year is also significantly higher by 0.75%.[15]

For a subperiod of our sample (2009-2019), we have information on the value of investment reported in firms' balance sheets (FICUS-FARE data set). When we relate, at the firm level, the value of investment as observed in this administrative data set and the value reported or forecasted by firms in the ECII survey, we also find very strong correlations (Columns 2 and 3). Overall, managers report in the manufacturing survey information on the value of

[15]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 $Inv_{i,t}^{R}$ as the latest number reported for the realized investment in year t and $Inv_{i,t}^{F}$ as the average of the four reported forecasts, to be consistent with our construction of the yearly forecast in the ECI survey.

investment which is eventually very close to what we can observe in the firms' balance sheet data set. 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 firms reporting stable employment.

Table 2: External consistency of ECI and ECII survey responses

	$\log Inv^R_{i,t}$	$\log Inv_{i,t}$	$\log Inv_{i,t}$	$\Delta \log K_{i,t}$	$\Delta \log K_{i,t}$	$\Delta \log EMP_{i,t}$
$\log Inv^F_{i,t}$	0.748***		0.608***	0.031***		
	(57.85)		(35.95)	(9.87)		
$\log Inv^R_{i,t}$		0.687***			0.035***	
		(49.69)			(12.26)	
$EMP^R_{i,t}$						0.029***
						(9.65)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N obs	28 609	13 878	13 878	19 507	19 452	18 465
N firms	4 527	2 712	2 712	3 505	3 487	3 508
R^2	0.89	0.91	0.88	0.12	0.12	0.07

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; it is originally collected at the product–quarter level and aggregated across products and quarters to obtain a firm–year measure. $\Delta \log EMP_{i,t}$ is the change in employees between $t-1$ and t observed in FICUS–FARE.

Appendix Table A7 provides evidence of internal consistency across different survey responses. It shows that firms expecting demand increases are also more likely to anticipate increases in production, prices, and employment, while firms forecasting demand decreases are less likely to expect increases in these 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.[16] This validation is crucial for our subsequent analysis of how expectation errors relate to resource allocation decisions.

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

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 subsequent 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 like age.

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***	0.057***	0.071***
	(11.93)	(3.62)	(5.04)	(6.63)	(5.70)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N obs	22 048	22 103	22 086	29 031	15 111
N firms	3 882	3 893	3 892	4 602	2 927
R^2	0.11	0.08	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. Regressions also include firm-level controls for age, size (number of employees), the leverage ratio, a dummy for the distribution of dividends in a given year t.

Column (1) shows a positive correlation between firms' qualitative survey answers on their own demand and their actual production growth as reported in their 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 on their own demand is 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 directly explore this hypothesis in the next section by examining the relationship between forecast errors and the dispersion in marginal revenue products of capital and labor.

3.3 FIRE deviations

A final necessary condition for expectation errors to result in misallocation is that these errors stem from frictions rather than shocks - which by nature are unpredictable. In this section, we present stylized facts showing that firms' expectations about their own business conditions deviate systematically from the full-information rational expectations (FIRE) benchmark.

Under the FIRE assumption, forecast errors should not be predictable using information that was in the manager's information set at the time the forecast was made. To test this deviation from FIRE, the usual tests consist of relating forecast errors to variables in the information set of the firm. We provide two standard tests (see also Born, Enders, Menkhoff, et al. (2024) or Ma et al. (2024) for similar evidence in different contexts). The first one consists of regressing forecast errors on forecast revision 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, $x^{FE}_{t+1} = x_{p,t+1} - F_{i,p,t}x_{p,t+1}$ is the forecast error of firm i for product p at date $t+1$ and $x^{FR}_{t} = F_{i,p,t-1}x_{p,t} - F_{i,p,t}x_{p,t+1}$ represents the forecast revision between $t-1$ and t.

We estimate the following two equations (2) and (3):

$$x^{FE}_{t+1} = \alpha + \beta\, x^{FR}_{t} + \varepsilon_{i,p,t} \tag{2}$$

$$x^{FE}_{t+1} = \alpha + \beta\, x^{FE}_{t} + \varepsilon_{i,p,t} \tag{3}$$

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

Columns (1) to (3) of Table 4 present the results of the first test for three key variables: demand, production, and prices. The coefficients are strongly negative and statistically significant in all cases. These results indicate that firms systematically overreact to news. When firms revise their forecasts downward between $t-1$ and t - that is, when $x^{FR}_{t} = F_{i,p,t-1}x_{p,t} - F_{i,p,t}x_{p,t+1}$ is positive - they tend to subsequently experience negative forecast errors. This indicates that they were too pessimistic ex post, suggesting that they overreacted to the new information that triggered the downward revision. This overreaction pattern is robust across all variables we examine and, as shown in Appendix Table A8 holds even after controlling for firm-level forecast revisions in aggregate output and inflation.[17]

Columns (4) to (6) of Table 4 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

[17] We also estimated Equation 2 separately for each firm and present in Appendix Figure A11 the distribution of the resulting β_i values.

forecast errors, and 0.030 for price forecast errors.[18] 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.

Table 4: 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*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Prod FE	Yes	Yes	Yes	No	No	No
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<0.05, ***p<0.01; ***p<0.001. Our dependent variables, $DMD^{FE}_{i,t+1}$, $PROD^{FE}_{i,t+1}$ and $PRICE^{FE}_{i,t+1}$ are the forecast error of a firm i about its own firm demand, production and price, computed as the difference between a forecast made in t and the declared realization in $t+1$. $DMD^{FR}_{i,t}$, $PROD^{FR}_{i,t}$ and $PRICE^{FR}_{i,t}$ are the forecast revision of a firm i about its own firm demand, production and price, computed as the difference between a forecast made in $t-1$ and a forecast made in t. Forecast errors and forecast revisions are at the product/quarter level.

This finding strongly contradicts the FIRE hypothesis, under which forecast revisions or past forecast errors should have no predictive power for forecast errors. Our results are consistent with similar results found in different contexts.[19] These systematic deviations from rational expectations are economically significant. Given that forecast errors influence firms' decisions as shown in Section 3.2, these systematic deviations from the FIRE hypothesis may potentially contribute to inefficient resource allocation.

[18] In Appendix Table A9, we provide results of regressions where we estimate the dynamic panel GMM estimation (Arrelano-Bover), allowing us to include firm fixed effects. Results are similar, the autocorrelation is positive and significant, except for prices.

[19] Appendix Table A8 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).

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.

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:

$$MRPK/L_{i,t} = \alpha_i + \alpha_{st} + \beta DMD^{FE}_{i,t} + \Gamma Z_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

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, $DMD^{FE}_{i,t}$ 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 firm size, its age category and its dividend payment status.[20]

One possible caveat with this empirical specification is that it does not allow us to identify a causal impact of forecast errors on misallocation since there is no obvious instrumental variable for forecast errors in our context. In particular, some unobserved variable may affect simultaneously MRPK (or MRPL) and forecast errors, leading to an endogeneity bias. To address this potential issue, 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 it covers allow us to control for stringent fixed effects.

Panel A of Table 5 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 an 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

[20] We detail in Appendix A the construction of these variables.

and returns to capital. The coefficient remains stable at 0.080, 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.

Table 5: Demand forecast errors and misallocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: $MRPK_{i,t}$			
	-	2-digit	2-digit	2-digit	3-digit	4-digit	Between
$DMD^{FE}_{i,t}$	0.091***	0.080***	0.053***	0.054***	0.050***	0.049***	0.091***
	(7.37)	(7.34)	(11.60)	(11.87)	(10.88)	(10.53)	(2.59)
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	6 240
N firms	6 307	6 303	5 198	5 143	5 128	5 053	6 240
R^2	0.002	0.05	0.84	0.85	0.88	0.89	0.14
				Panel B: $MRPL_{i,t}$			
	-	2-digit	2-digit	2-digit	3-digit	4-digit	Between
$DMD^{FE}_{i,t}$	0.073***	0.073***	0.043***	0.041***	0.040***	0.039***	0.095***
	(15.46)	(15.72)	(13.71)	(13.54)	(12.53)	(12.26)	(7.44)
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	6 296
N firms	6 395	6 391	5 256	5 180	5 165	5 090	6 296
R^2	0.01	0.03	0.61	0.62	0.66	0.67	0.20

Note: Robust t-stats in parentheses clustered at the firm level. **p<0.05, ***p<0.01; ***p<0.001. We report results of OLS regressions relating firm-level MRPK (Panel A) and MPRL (Panel B) to $DMD^{FE}_{i,t}$ the forecast error of a firm i about its own firm demand, computed as the difference between a forecast made in $t-1$ and the declared realization in t. This forecast error is initially at the product/quarter level and is aggregated across products and year to obtain a firm*year measure. In each panel, the columns correspond to different regressions: in Column 1, the regressions do not include any controls or fixed effects, in Column 2 sector*year fixed effects are included (at level 2 of the sector classification), in Column 3 firm fixed effects are included, Column 4 other firm time-varying controls are added, in Columns 5 and 6 the sector*year fixed effects are computed using a more disaggregate definition of sector, and in Column 7, we run regressions using firm-level average values of the variables of the model (calculated over the period each firm is observed in the survey).

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, effectively 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) - our baseline specification - further strengthens our identification of the estimated coefficient by controlling for time-varying firm controls (including firm size, age category, and dividend payment status). These variables capture dynamic 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 add these controls, our result still holds: 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 insufficiently granular industry definitions, Columns (5) and (6) employ increasingly fine-grained sector*year fixed-effects. Column (5) uses 3-digit sector*year fixed-effects, while Column (6) uses 4-digit sector*year fixed-effects, comparing firms within very narrowly defined industries facing almost identical market conditions. The stability of the coefficients (0.050 and 0.049, respectively) in these two specifications confirms our previous results with less disaggregated definition of sectors — firms with different forecast errors exhibit different levels of MRPK even when they operate in nearly identical market environments.

Finally, Column (7) estimates Equation (4) 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. Appendix Figure A12 plots this positive relationship across firms.

Panel B of Table 5 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.

Appendix Table A10 provides two robustness checks. In the first one we include as controls the lagged value of the demand forecast error, since we showed that forecast errors are persistent. In the second specification, we control for forecast errors for all variables other than demand. This accounts for a firm's manager's general forecasting ability, which serves as a measure of managerial skill. Indeed, Bloom, Kawakubo, et al. (2021) document that managers who form more accurate expectations also manage their firms more effectively, and Hsieh, Hurst, et al. (2019) show that the allocation of skills accounts for a substantial share of aggregate productivity. By doing so, we isolate the specific effect of the firm's demand forecast error over and above the manager's general ability to form expectations. Our main result holds in these two robustness check: the coefficient is still statistically significant and is close to the one we obtain in our baseline case for both MRPK and MRPL.

Table A11 provides several robustness tests related to the alternative specifications of the dependent variables or regressors and the sample of firms. In all specifications, we find a positive and significant correlation between the demand forecast errors and MRPK or MPRL with very small variation in estimated coefficient.[21]

Finally, Appendix Table A12 examines 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 marginal revenue products of capital (MRPK) and labor (MRPL), whereas optimistic errors are associated with lower MRPK and MRPL — highlighting that both under- and overestimation of demand contribute to resource misallocation.

Overall, our results suggest that MRPK and MRPL are lower when firms are too optimistic about their own demand and higher when they are too pessimistic. Our estimates indicate that moving from one forecast error category to another (e.g., from "accurate" to "underpredicting") is associated with a 5.4% change in MRPK and a 4.1% change in MRPL, and these effects are highly significant. Although the explained dispersion in MRPK/L appears relatively small (0.3% and 1% respectively), this likely reflects the intrinsic limitations of qualitative expectations, which inherently capture only a subset of the true variation in forecast errors[22]. In addition, contributions to misallocation measured using firm-level data are usually of similar magnitude. Using European firm data, Gorodnichenko et al. (2025) report contributions of comparable size across a range of factors that could explain factor misallocation.

4.2 Dynamic effects

While our baseline results establish a contemporaneous relationship between forecast errors and misallocation, a key question is how persistent these effects are 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 trace the dynamic response of MRPK and MRPL to demand forecast errors over multiple time horizons without imposing restrictive assumptions about the underlying dynamics.

[21] In particular, one potential concern is that firms when expecting an increase in their demand may also increase their prices so that ex post the demand does not increase. In our set-up, this would generate a difference between expected and realized demand which could not be attributed to a forecast error. In column (9) of Table A11, we estimate a regression controlling for past price changes as reported by firms to overcome this concern and our result still holds.

[22] More generally, as it is frequently the case when we use granular data, any measurement error in the demand forecast error or in our measures of MRPK/L will attenuate R^2.

For each horizon h from 0 to 6 years, we estimate the following Equation 5:

$$MRPK/L_{i,t+h} = \alpha_i^h + \alpha_{st}^h + \beta^h DMD_{i,t}^{FE} + \Gamma^h Z_{i,t-1} + \varepsilon_{i,t+h} \tag{5}$$

where $MRPK/L_{i,t+h}$ is either the marginal revenue product of capital or labor of firm i at time $t+h$, α_i^h denotes firm fixed-effects, α_{st}^h represents sector*time fixed-effects, $DMDFE_{i,t}$ 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 time horizons.

Table 6: Demand Forecast Errors and MRPK/L: Local projections

	t	t+1	t+2	t+3	t+4	t+5	t+6
	Panel A: $MRPK_{i,t}$						
$DMD_{i,t}^{FE}$	0.054***	0.044***	0.024***	0.021***	0.022***	0.018**	0.008
	(11.87)	(8.14)	(3.85)	(3.18)	(2.69)	(2.51)	(0.97)
FE+Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.85	0.86	0.86	0.86	0.85	0.85	0.85
	Panel B: $MRPL_{i,t}$						
$DMD_{i,t}^{FE}$	0.041***	0.031***	0.018***	0.016***	0.010*	0.006	0.005
	(13.54)	(8.90)	(4.41)	(3.18)	(1.82)	(1.06)	(0.79)
FE+Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.62	0.63	0.62	0.62	0.62	0.63	0.62

Note: Robust t-stats in parentheses clustered at the firm level. *p<0.05, **p<0.01; ***p<0.001. The table reports results of local projection estimations relating firm-level MPRK (Panel A) or MPRL (Panel B) measured at different year horizons $t+h$ and the demand forecast error $DMD_{i,t}^{FE}$ measured at year t Our dependent variable of interest. Sector*year and firm fixed effects and firm-level time-varying controls (like age, size...) are also included.

Table 6 reports the dynamic response of MRPK and MRPL 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.[23]

[23] In Appendix Table A13, as robustness, 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

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.[24] This persistence can indicate that labor adjustments in response to forecast errors are faster than capital adjustments. This differential persistence between capital and labor misallocation provides insights into the relative importance of various adjustment frictions. The more rapid decay of forecast error effects on MRPL compared to MRPK indicates that capital adjustment costs, are more binding over longer horizons than labor market frictions.

The persistent effects of forecast errors on misallocation highlight the importance of accurate expectations for efficient resource allocation. Our results suggest that even temporary errors in forecasting can have long-lasting impacts on firm productivity. This result shows that forecast errors interact with real frictions in the economy — such as adjustment costs or irreversibility — amplifying the costs and prolonging the effects of such mistakes.[25] 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.

4.3 Alternative drivers of misallocation

While our analysis establishes a link between forecast errors and misallocation, the literature has identified several other important drivers of misallocation. In this section, we investigate how these established mechanisms interact with the forecast error channel we identify.

Theoretical and empirical research has emphasized three primary channels through which misallocation may arise: financial frictions, labor market rigidities, and technological constraints. Financial frictions can prevent efficient capital allocation when firms with high returns to capital cannot obtain financing to expand, while firms with excess capital face little pressure to reallocate resources. Labor market frictions, including hiring/firing costs and regulations, may similarly distort firms' employment decisions, creating wedges between marginal revenue products across firms. Technological constraints, including adjustment costs and indivisibility in capital goods, can further impede efficient resource allocation by preventing firms from reaching their optimal scale.

Table 7 reports estimates from regressions incorporating empirical proxies for these alternative explanations. Column (1) reproduces our baseline specification from Table 5, showing that a one-unit increase in demand forecast errors is associated with a 5.4% increase in MRPK.

obtained for horizons t and $t+1$ but the effect of demand errors in year t is also persistent and still significant at years $t+2$, $t+3$ and $t+4$ for both MRPK and MRPL.

[24] We show in Appendix Table A13 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.

[25] 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.

Table 7: Alternative drivers of MRPK misallocation

	(1)	(2)	(3)	(4)	(5)
$DMD^{FE}_{i,t}$	0.054***	0.051***	0.051***	0.050***	0.050***
	(11.87)	(11.62)	(11.70)	(10.93)	(10.68)
Leverage		-0.509***	-0.506***	-0.492***	-0.499***
		(-17.09)	(-16.96)	(-14.64)	(-14.69)
Financial constraints (production)			-0.019**	-0.009	-0.011
			(-2.51)	(-1.01)	(-1.23)
Financial constraints (investment)				-0.010***	-0.009***
				(-3.24)	(-2.71)
Technological constraint (investment)					-0.008**
					(-2.38)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
N obs	33 523	33 191	33 191	25 313	24 622
N firms	5 143	5 109	5 109	4 244	4 169
R^2	0.85	0.85	0.85	0.86	0.86

Note: Robust t-stats in parentheses clustered at the firm level. $^{**}p<0.05$, $^{***}p<0.01$; $^{***}p<0.001$. The table reports results of regressions linking $MRPK_{i,t}$ the marginal revenue of capital of firm i in year t (calculated as the log-ratio of value added over capital) to $DMD^{FE}_{i,t}$ which is the forecast error of a firm i about its own demand, computed as the difference between a forecast made in $t-1$ and the declared realization in t. This forecast error is initially at the product/quarter level and is aggregated across products and year, so the dependent variable is at the firm/year level.

In Column (2), we introduce firm leverage as a proxy for financial constraints. We find that higher leverage is strongly associated with lower MRPK. Importantly, including this control reduces the coefficient on forecast errors only slightly (to 0.051), suggesting our main effect is not simply capturing heterogeneity in firms' financial situations. Column (3) adds a direct measure of financial constraints from the ECI survey, where firms report whether their production is limited by financial factors. This captures firms' self-reported financial constraints rather than just inferring them from balance sheet measures. The coefficient (-0.019) indicates that financially constrained firms have systematically lower MRPK, consistent with a mechanism where these firms would like to expand but cannot access sufficient capital. The forecast error coefficient remains stable at 0.051, indicating that these are distinct channels.

Column (4) presents our most comprehensive specification, which includes a measure of technological constraints from the ECII survey. This variable captures whether firms report their investment is limited by technological factors, such as installation costs, indivisibility, or time-to-build lags. The negative coefficient (-0.008) suggests that firms facing technological barriers tend to have lower MRPK, consistent with models where adjustment costs create wedges between marginal revenue products. Even after controlling for all these alternatives, the forecast error coefficient remains consistently at 0.050.

The stability of the demand forecast error coefficient across specifications indicates that expectation errors represent an additional and complementary channel of misallocation that operates independently of traditional frictions. Firms make investment decisions based on expected future demand, and even in the absence of financial or technological constraints, errors in these forecasts would still generate dispersion in marginal revenue products.

In a similar spirit, Appendix Table A14 explores whether the relationship between forecast errors and labor misallocation persists after accounting for labor market frictions. The results show that even when controlling for recruitment difficulties —- both general and segmented by worker type -—, the positive association between demand forecast errors and MRPL remains robust. Specifically, firms that report difficulties in hiring workers tend to have higher MRPL, consistent with the idea that labor market rigidities contribute to misallocation. However, the coefficient associated with forecast errors remains stable and significant in all specifications, indicating that forecast errors represent an independent and complementary source of labor misallocation, distinct from traditional labor market frictions.

Although many policy interventions focus on alleviating financial constraints or reducing regulatory barriers, our results suggest that improving firms' forecasting abilities could provide an additional avenue for enhancing resource allocation, particularly for smaller firms that may lack sophisticated forecasting teams.[26] This is consistent with Gorodnichenko et al. (2025), who show that other firm characteristics - such as resource utilization and the dynamic adjustment of inputs - play a central role in determining marginal returns to factors. Our mechanism may help explain part of their findings: a firm's ability to form accurate forecasts can shape its allocation of resources and its responsiveness to changing conditions, ultimately influencing its marginal returns.

4.4 The predictable component of forecast errors

In this section, we show that MRPK and MRPL dispersion is driven — at least in part — by predictable demand forecast errors, reflecting inefficient dispersion. This distinction is important for deriving policy recommendations.

In Section 3.3, we show that forecast errors can be predicted on average, suggesting a violation of the FIRE hypothesis. We now decompose the forecast error into predictable and unpredictable components. We find that a large share of forecast errors can be predicted using a simple vector of variables from the firm's information set.[27]

Formally, we estimate Equation 6, where Θ is a vector of variables in the information set of firm i at time t. Consistent with our previous results, we find that $\beta \neq 0$. We also show that this vector has substantial explanatory power.

$$x^{FE}_{i,p,t+h} = \alpha + \beta\, \Theta_{i,p,t} + \varepsilon_{i,p,t} \tag{6}$$

[26] Even if these forecasting errors may be hard to eliminate as shown by bloom$_r$$ationalizing_2$025.

[27] 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.

We estimate Equation 6 at the quarterly frequency using three different models. In these empirical exercises, Θ will include one lag of $DMD_{i,t}^{FE}$, the variation in value added, the variation in production, and backlog of orders.

In the first model, we run the regression using our full sample of firms, measuring average correlations, and assuming that all firms use the same β in the forecasting model. In the second model, we estimate the equation for each sector separately, using the same variables but allowing β to differ across sectors in the forecast model. In the third exercise, we run the regression at the firm level relying on the long panel dimension of our data set, we use the same variables as in previous regressions but we allow the β forecast model to differ across firms.[28] When estimated on all firms in our sample, we find that, on average, 31% of the variance in forecast errors can be explained in our regressions.[29] Appendix Figure A13 presents the distribution of R^2 resulting from the sector-level and the firm-level estimation. All three exercises provide consistent evidence that firms make predictable expectation errors, as roughly one-third of the forecast errors can be predicted using a small set of variables. We interpret this finding as evidence that at least one-third of the effect of forecast errors on marginal returns, presented in Section 4, is driven by predictable errors — i.e. deviations from rational expectations. The remaining two-thirds likely arise from forecast errors caused either by inherently unpredictable shocks or by errors that, in theory, could have been anticipated but only with an expanded set of predictors or a more refined modeling framework. Consequently, our estimate of the deviation from rational expectations should be interpreted as a conservative lower-bound estimate of the true effect.

To investigate the role of predictable versus unpredictable components of forecast errors on misallocation, we estimate the following Equation (7) using the fitted values ($DMD_{i,t}^{FE,Pred}$) as the predictable component of forecast errors and the residuals ($DMD_{i,t}^{FE,Unpred}$) of Equation 6 as the unpredictable shock component of forecast errors:

$$MRPK/L_{i,t} = \alpha_i + \alpha_{st} + \beta^{Pred}\, DMD_{i,t}^{FE,Pred} + \beta^{Unpred}\, DMD_{i,t}^{FE,Unpred} + \Gamma Z_{i,t-1} + \varepsilon_{i,t} \qquad (7)$$

Table 8 presents the results of this regression for the pooled, sector-level and firm-level regressions. Column (1) of Table 8 reports our baseline estimates from Table 5. We standardize the demand forecast error and its two components to ease the comparison between estimated coefficients.[30] A one standard deviation increase in demand forecast errors is associated with a 0.030 standard-deviation increase in (MRPK) and a 0.056 standard-deviation increase in (MRPL). Columns (2)–(4) for MRPK and columns (5)–(7) for MRPL break down these effects into a predictable component and an idiosyncratic shock component, depending on

[28] We keep only firms with more than 20 quarterly observations.

[29] Appendix Table A15 presents the result of this first regression.

[30] 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).

the forecasting model employed. 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 0.024 for MRPL. 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.

Table 8: Exploring the effect of the predictable component

	$MRPK_{i,t}$				$MRPL_{i,t}$			
	Baseline	Pooled	Sector	Firm	Baseline	Pooled	Sector	Firm
$DMD^{FE}_{i,t}$	0.030***				0.056***			
	(10.60)				(12.21)			
$DMD^{FE}_{i,t}$ *Predictable*		0.012***	0.010***	0.016***		0.020***	0.016***	0.022***
		(3.63)	(3.00)	(4.19)		(4.09)	(3.27)	(3.39)
$DMD^{FE}_{i,t}$ *Unpredictable*		0.021***	0.024***	0.016***		0.041***	0.045***	0.040***
		(7.41)	(9.14)	(5.20)		(9.35)	(11.39)	(8.05)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	27 860	27 860	27 854	17 454	27 963	27 963	27 957	17 483
N firms	4 520	4 520	4 520	1 885	4 554	4 554	4 554	1 897
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 5 with the key variables normalized by their standard deviations. In Column (2) and (6), Equation 7 uses the fitted values ($DMD^{FE}_{i,t}$ *Predictable*) and residuals ($DMD^{FE}_{i,t}$ *Unpredictable*) of Equation 6 estimated over all firms pooled. In Column (3) and (7), $DMD^{FE}_{i,t}$ *Pred* and $DMD^{FE}_{i,t}$ *Unpred* come from Equation 6 estimated for each sector. In Column (4) and (8), Equation 6 has been estimated for each firm (keeping only firms with at least 20 observations).

These findings reveal that forecast error-driven misallocation is driven, at least in part, by deviations from full information rational expectations (FIRE). The significant coefficients on the predictable components indicate that firms could potentially improve their resource allocation by addressing systematic biases in their forecasting processes.

5 Inspecting the mechanism

The intuition behind our main result is that when a firm expects an increase in demand, it anticipates an increase in production (as shown in Appendix A7). Consequently, it invests more (as also demonstrated in Table 3), and hire more to expand production capacity. However, if actual demand falls short of expectations, the firm may have been overly optimistic, leading to an inflated capital stock and workforce compared to similar firms, thereby resulting in 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 observed 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.[31]

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			
	$Inv^F_{i,t-1}$	$Inv^R_{i,t-1}$	$Inv_{i,t-1}$	$\Delta EMP_{i,t-1}$	$MRPK_{i,t}$	$MRPK_{i,t}$	$MRPK_{i,t}$	$MRPL_{i,t}$
$DMD^{FE}_{i,t}$	-0.045***	-0.061***	-0.076***	-0.010***				
	(-3.21)	(-4.04)	(-2.99)	(-3.09)				
Fitted $Inv^F_{i,t-1}$					-0.999***			
					(-8.24)			
Fitted $Inv^R_{i,t-1}$						-0.746***		
						(-8.58)		
Fitted $Inv_{i,t-1}$							-0.551***	
							(-5.72)	
Fitted $\Delta EMP_{i,t-1}$								-3.602***
								(-8.28)
Sector*Year FE	.	.	.	.	Yes	Yes	Yes	Yes
Firm FE	.	.	.	.	Yes	Yes	Yes	Yes
Firm controls	.	.	.	.	Yes	Yes	Yes	Yes
N obs	21 044	21 267	9 860	16 609	19 289	19 493	9 519	15 209
N firms	3 642	3 664	2 189	3 041	3 469	3 495	2 126	2 900
R^2	0.86	0.82	0.85	0.06	0.86	0.86	0.90	0.66

Note: Robust t-stats in parentheses clustered at the firm level. $^{**}p<0.05$, $^{***}p<0.01$; $^{***}p<0.001$. 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 $DMD^{FE}_{i,t}$. 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.

[31] This exercise is not an IV regression for which we would assume that demand forecast errors (at date t) are an instrumental variable for investment or employment decisions (at date $t-1$ and results can not be read as causal. Our objective is to provide more insights on how forecast errors, investment and employment decisions and MRPK/L are correlated.

Columns (5) to (8) show the results of estimations where we use the fitted values of investment or employment from the previous regressions (ie 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.

Production Capacity and Inventories. 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 production 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 produce too little, resulting in insufficient production capacity and use inventory to meet realized demand. Both scenarios reflect inefficient allocation of resources and contribute to dispersion in marginal returns.

Table 10: Demand Forecast Errors, Production Capacity and Inventories

	Step 1		Step 2	
	$Q_{\text{ProdCap},i,t}$	$Q_{\text{Invent},i,t}$	$MRPK_{i,t}$	$MRPK_{i,t}$
$DMD^{FE}_{i,t}$	-0.049***	-0.086***		
	(-8.87)	(-12.05)		
Fitted Q_{ProdCap}			-1.042***	
			(-11.50)	
Fitted Q_{Invent}				-0.555***
				(-8.94)
Sector*Year FE	.	.	Yes	Yes
Firm FE	.	.	Yes	Yes
Firm controls	.	.	Yes	Yes
N obs	35 632	22 989	32 589	21 012
N firms	5 280	3 767	5 044	3 596
R^2	0.37	0.27	0.85	0.86

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 $DMD^{FE}_{i,t}$. 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.

To further investigate the role played by production capacity and inventories we examine how forecast errors affect MRPK trough their effect on firms' self-reported production capacity constraints and inventories. Table 10 presents results from our two-step empirical strategy presented above. Q_{ProdCap} reports quantitative to the following ECII 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)*" and Q_{Invent} "*Do you consider that, given the season, your current stocks of manufactured products are above normal (1), normal (0), or below normal (-1)?*"

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 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

This paper explores the link between firms' expectation errors and resource misallocation. Using a rich dataset combining French firm surveys and administrative data, we show that heterogeneity in firms' forecast errors contributes significantly to the observed dispersion in marginal revenue products of capital and labor within narrowly defined industries.

Our analysis yields several important findings. First, firms systematically deviate from rational expectations, with evidence of overreaction to news about their own business conditions. Second, these expectations significantly influence firms' investment, production, and employment decisions. Third, demand forecast errors are correlated with marginal return of factors: firms underestimating their demand experiencing significantly higher MRPK and MRPL. 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%. Fourth, a large share of these demand forecast errors can be predicted, which implies that the resulting dispersion in returns is inefficient. Fifth, the impact of forecast errors persists over multiple years, with different adjustment patterns for capital versus labor.

These results have several implications. From a theoretical perspective, our findings highlight the importance of incorporating non-rational expectation formation into models of firm dynamics and resource allocation. The standard assumption that firms optimize under rational expectations misses one source of heterogeneity that contributes to observed misallocation.

From a policy standpoint, our results suggest that improving the quality of information available to firms and enhancing their forecasting capabilities could improve resource allocation. The persistent nature of forecast error effects, indicates that such improvements could have some benefits for aggregate productivity.

References

Aghion, Philippe, Robin Burgess, Stephen J Redding, and Fabrizio Zilibotti (2008). "The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India". *American Economic Review* 98.4, pp. 1397–1412.

Albrizio, Silvia, Beatriz González, and Dmitry Khametshin (2023). "A Tale of Two Margins: Monetary Policy and Capital Misallocation".

Alpysbayeva, Dinara and Stijn Vanormelingen (2022). "Labor market rigidities and misallocation: Evidence from a natural experiment". *Labour Economics* 78. Publisher: Elsevier BV, p. 102229.

Andrade, Philippe, Olivier Coibion, Erwan Gautier, and Yuriy Gorodnichenko (2022). "No firm is an island? How industry conditions shape firms' expectations". *Journal of Monetary Economics* 125, pp. 40–56.

Angeletos, G.-M. and C. Lian (2016). "Incomplete Information in Macroeconomics". *Handbook of Macroeconomics*. Vol. 2. Elsevier, pp. 1065–1240.

Angeletos, George-Marios, Zhen Huo, and Karthik A Sastry (2021). "Imperfect Macroeconomic Expectations: Evidence and Theory". *NBER Macroeconomics Annual* 35.1, pp. 1–86.

Asker, John, Allan Collard-Wexler, and Jan De Loecker (2014). "Dynamic Inputs and Resource (Mis)Allocation". *Journal of Political Economy* 122.5, pp. 1013–1063.

Asriyan, Vladimir and Alexandre Kohlhas (2025). "The Macroeconomics of Data: Scale, Product Choice, and Pricing in the Information Age".

Bachmann, Rüdiger and Steffen Elstner (2015). "Firm optimism and pessimism". *European Economic Review* 79, pp. 297–325.

Bachmann, Rüdiger, Steffen Elstner, and Eric R Sims (2013). "Uncertainty and Economic Activity: Evidence from Business Survey Data". *American Economic Journal: Macroeconomics* 5.2, pp. 217–249.

Banerjee, Abhijit V. and Benjamin Moll (2010). "Why Does Misallocation Persist?" *American Economic Journal: Macroeconomics* 2.1, pp. 189–206.

Barrero, Jose Maria (2022). "The micro and macro of managerial beliefs". *Journal of Financial Economics* 143.2, pp. 640–667.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta (2013). "Cross-Country Differences in Productivity: The Role of Allocation and Selection". *American Economic Review* 103.1, pp. 305–334.

Bau, Natalie and Adrien Matray (2023). "Misallocation and Capital Market Integration: Evidence From India". *Econometrica* 91.1, pp. 67–106.

Bhandari, Anmol, Serdar Birinci, Ellen R McGrattan, and Kurt See (2020). "What Do Survey Data Tell Us about US Businesses?" *American Economic Review: Insights* 2.4, pp. 443–58.

Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni L. Violante (2022). "Firm and Worker Dynamics in a Frictional Labor Market". *Econometrica* 90.4, pp. 1425–1462.

Bils, Mark, Peter J. Klenow, and Cian Ruane (2021). "Misallocation or Mismeasurement?" *Journal of Monetary Economics* 124, S39–S56.

Bloom, Nicholas, Mihai Codreanu, and Robert Fletcher (2025). *Rationalizing Firm Forecasts*.

Bloom, Nick, Stephen Bond, and John Van Reenen (2007). "Uncertainty and Investment Dynamics". *The Review of Economic Studies* 74.2, pp. 391–415.

Bloom, Nick, Takafumi Kawakubo, Charlotte Meng, Paul Mizen, Riley Rebecca, and Tatsuro Senga (2021). "Do Well Managed Firms Make Better Forecasts?" *NBER Working Paper Series* 29591.

Boneva, Lena, James Cloyne, Martin Weale, and Tomasz Wieladek (2020). "Firms' Price, Cost and Activity Expectations: Evidence from Micro Data". *The Economic Journal* 130.627, pp. 555–586.

Born, Benjamin, Zeno Enders, Manuel Menkhoff, Gernot J Müller, and Knut Niemann (2024). "Firm Expectations and News: Micro v Macro".

Born, Benjamin, Zeno Enders, and Gernot J Müller (2023). "On FIRE, news, and expectations".

Born, Benjamin, Zeno Enders, Gernot J. Müller, and Knut Niemann (2023). "Firm expectations about production and prices: facts, determinants, and effects". *Handbook of Economic Expectations*. Elsevier, pp. 355–383.

Brynjolfsson, Erik and Kristina McElheran (2016). "The Rapid Adoption of Data-Driven Decision-Making". *American Economic Review* 106.5, pp. 133–139.

Buera, Francisco J. and Yongseok Shin (2013). "Financial Frictions and the Persistence of History: A Quantitative Exploration". *Journal of Political Economy* 121.2, pp. 221–272.

Chen, Cheng, Tatsuro Senga, Chang Sun, and Hongyong Zhang (2023). "Uncertainty, imperfect information, and expectation formation over the firm's life cycle". *Journal of Monetary Economics* 140, pp. 60–77.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico (2023). "Monetary Policy, Corporate Finance, and Investment". *Journal of the European Economic Association* 21.6, pp. 2586–2634.

Coibion, Olivier and Yuriy Gorodnichenko (2012). "What Can Survey Forecasts Tell Us about Information Rigidities?" *Journal of Political Economy* 120.1, pp. 116–159.

Coibion, Olivier and Yuriy Gorodnichenko (2015). "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts". *American Economic Review* 105.8.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele (2020). "Inflation Expectations and Firm Decisions: New Causal Evidence". *The Quarterly Journal of Economics* 135.1, pp. 165–219.

David, Joel M, Lukas Schmid, and David Zeke (2022). "Risk-Adjusted Capital Allocation and Misallocation". *Journal of Financial Economics* 145.3, pp. 684–705.

David, Joel M., Hugo A. Hopenhayn, and Venky Venkateswaran (2016). "Information, Misallocation, and Aggregate Productivity". *The Quarterly Journal of Economics* 131.2, pp. 943–1005.

David, Joel M. and Venky Venkateswaran (2019). "The Sources of Capital Misallocation". *American Economic Review* 109.7, pp. 2531–2567.

Decker, Ryan A, John C Haltiwanger, Ron S Jarmin, and Javier Miranda (2020). "Changing Business Dynamism and Productivity: Shocks versus Responsiveness". *American Economic Review* 110.12, pp. 3952–90.

Enders, Zeno, Franziska Hünnekes, and Gernot J Müller (2022). "Firm expectations and economic activity." *Journal of the European Economic Association* 20.6, pp. 2396–2439.

Gorodnichenko, Yuriy, Debora Revoltella, Jan Svejnar, and Christoph T Weiss (2025). "Resource Misallocation in European Firms: The Role of Constraints, Firm Characteristics and Managerial Decisions".

Heise, Sebastian and Tommaso Porzio (2022). "Labor Misallocation Across Firms and Regions". *NBER Working Paper Series* 30298.

Hopenhayn, Hugo A. (2014). "Firms, Misallocation, and Aggregate Productivity: A Review". *Annual Review of Economics* 6.1, pp. 735–770.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones, and Peter J. Klenow (2019). "The Allocation of Talent and U.S. Economic Growth". *Econometrica* 87.5, pp. 1439–1474.

Hsieh, Chang-Tai and Peter J Klenow (2009). "Misallocation and Manufacturing TFP in China and India". *Quarterly Journal of Economics*, p. 46.

Jordà, Òscar (2005). "Estimation and Inference of Impulse Responses by Local Projections". *American Economic Review* 95.1, pp. 161–182.

Karabarbounis, Marios and Patrick Macnamara (2021). "Misallocation and financial frictions: The role of long-term financing". *Review of Economic Dynamics* 40, pp. 44–63.

Ma, Yueran, Tiziano Ropele, David Sraer, and David Thesmar (2024). "A Quantitative Analysis of Distortions in Managerial Forecasts".

Massenot, Baptiste and Yuri Pettinicchi (2018). "Can firms see into the future? Survey evidence from Germany". *Journal of Economic Behavior & Organization* 145, pp. 66–79.

Midrigan, Virgiliu and Daniel Yi Xu (2014). "Finance and Misallocation: Evidence from Plant-Level Data". *American Economic Review* 104.2, pp. 422–458.

Moll, Benjamin (2014). "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review* 104.10, pp. 3186–3221.

Restuccia, Diego and Richard Rogerson (2008). "Policy distortions and aggregate productivity with heterogeneous establishments". *Review of Economic Dynamics* 11.4, pp. 707–720.

Ropele, Tiziano, Yuriy Gorodnichenko, and Olivier Coibion (2024). "Inflation Expectations and Misallocation of Resources: Evidence from Italy". *American Economic Review: Insights* 6.2, pp. 246–261.

Senga, Tatsuro (2018). "A New Look at Uncertainty Shocks: Imperfect Information and Misallocation".

Su, Hsuan-Li (2024). "Financial Frictions, Capital Misallocation, and Input-Output Linkages". *American Economic Journal: Macroeconomics* 16.2, pp. 62–94.

Tanaka, Mari, Nicholas Bloom, Joel M. David, and Maiko Koga (2020). "Firm performance and macro forecast accuracy". *Journal of Monetary Economics* 114, pp. 26–41.

Zorn, Peter (2020). "Investment Under Rational Inattention: Evidence from US Sectoral Data". *CESifo Working Paper* 8436.

APPENDIX

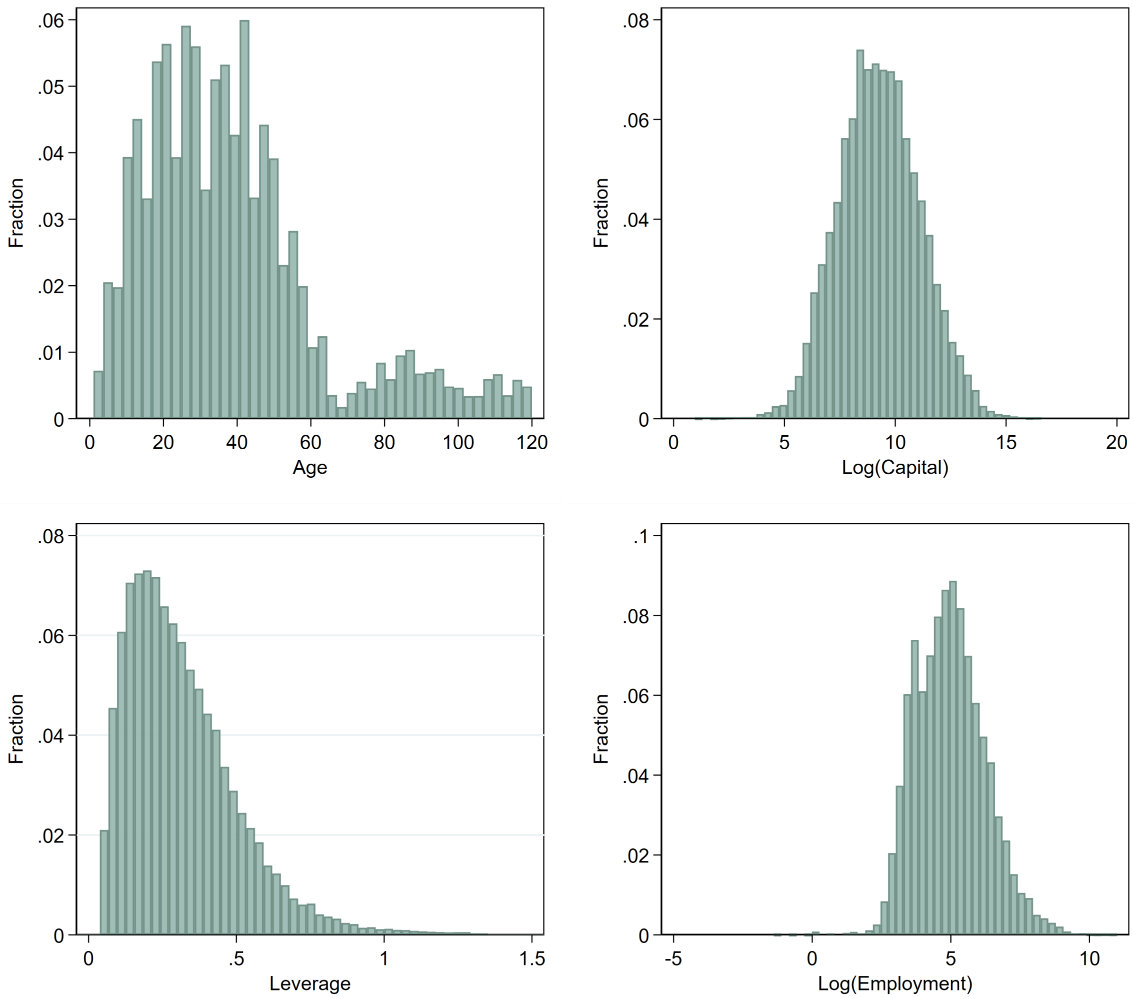
A Balance sheet data (FICUS/FARE)

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 payment status	Dummy Dividend > 0
Production	Total Production
Capital	Tangible capital
Value-Added	Value-Added At Factor Cost
Wage (W_t)	Total Compensation of Employee
MRPK	$\log \frac{VA_t}{K_t}$
MRPL	$\log \frac{VA_t}{W_t}$

Note: MRPK and MRPL are trimmed at 1% at the top and bottom of the distribution.

Figure A1: Distribution of various firm characteristics



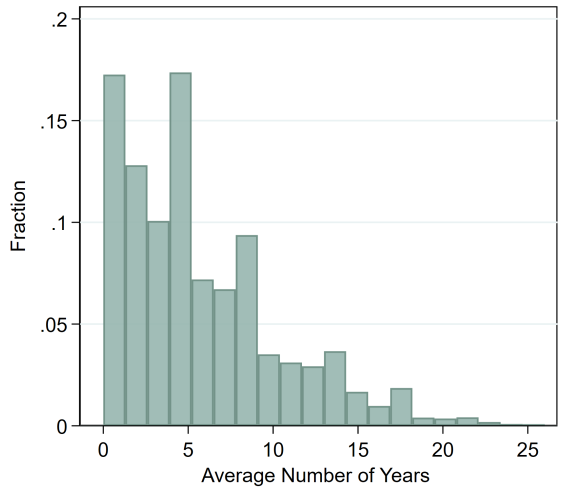
Note: This figure shows the distribution of firm age (upper left), firm size (upper right), firm leverage (bottom left) and firm investment rate (bottom right) in our sample. The distributions are obtained using variables from the balance sheet data set FICUS-FARE.

Figure A2: Evolution of misallocation measures over time

Note: This figure shows the evolution across time in capital and labor misallocation measures.

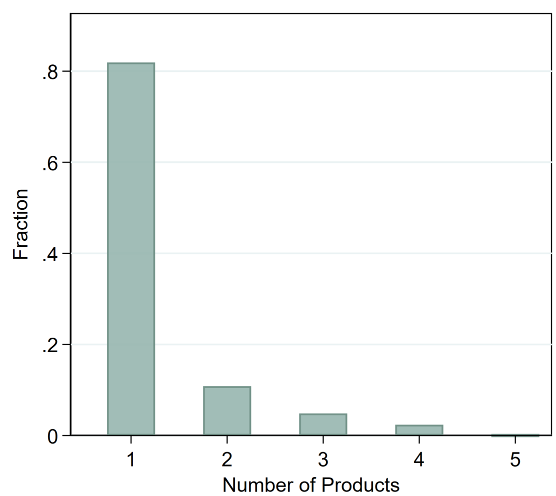
B Survey expectation data (ECI & ECII)

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



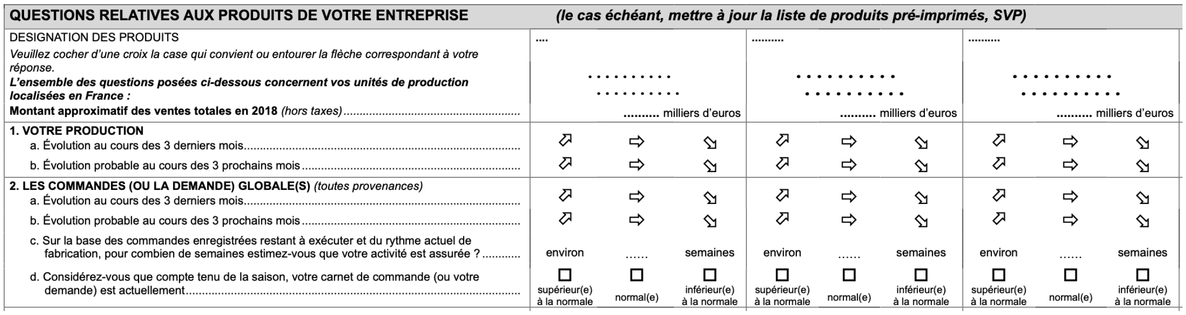
Note: This figure plots the distribution of the number of years during which firms report expectations and realizations of prices, demand and output.

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 A2: 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

Since firms report different expectations for each of their products, we weight the expectation by the share of each product's revenue to the firm's total revenue. This method enables us to compute an expectation for each firm and each quarter. Finally, to align the frequency of these expectation errors with our second source of firm-level data, we compute the annual average of these quarterly expectations.

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 A3: 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

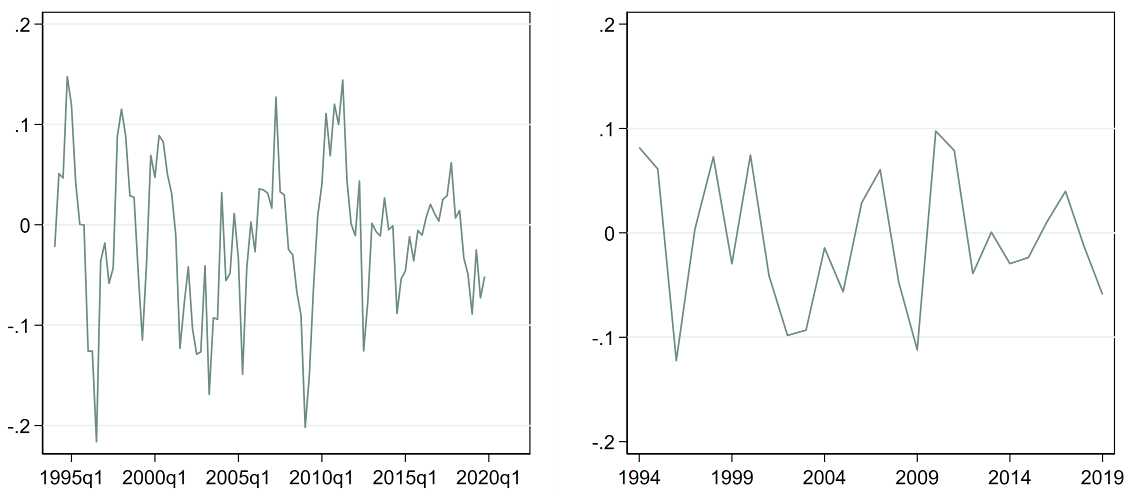
Firms are asked to report their investment plan for a given year in January, April, July and October. We take the average of these quarterly expectations over each year to compute our measure of investment expectation in a given year.

Table A4: 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

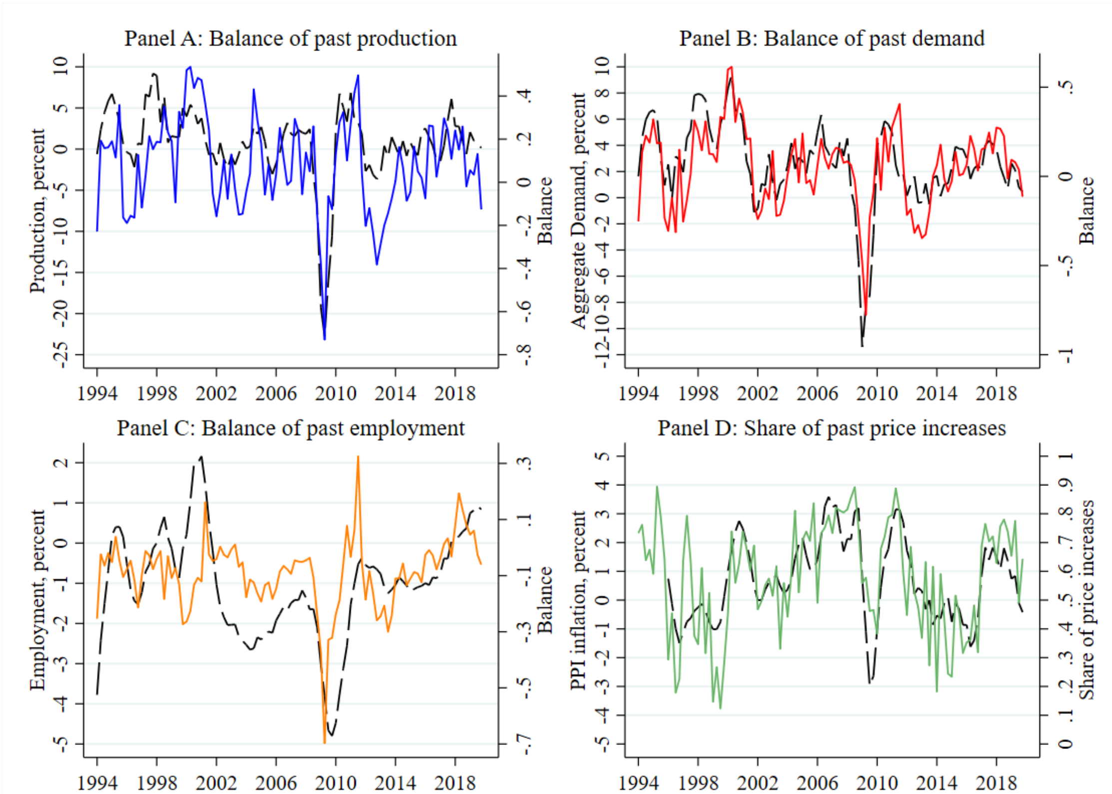
Note: Average proportion of qualitative categories reported by firms' managers when answering the different questions of the ECI survey. The questions cover their own prices and output and the demand addressed to their own products. Calculations have been made using the quarterly frequency data sets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

Figure A7: Evolution of forecast errors over time



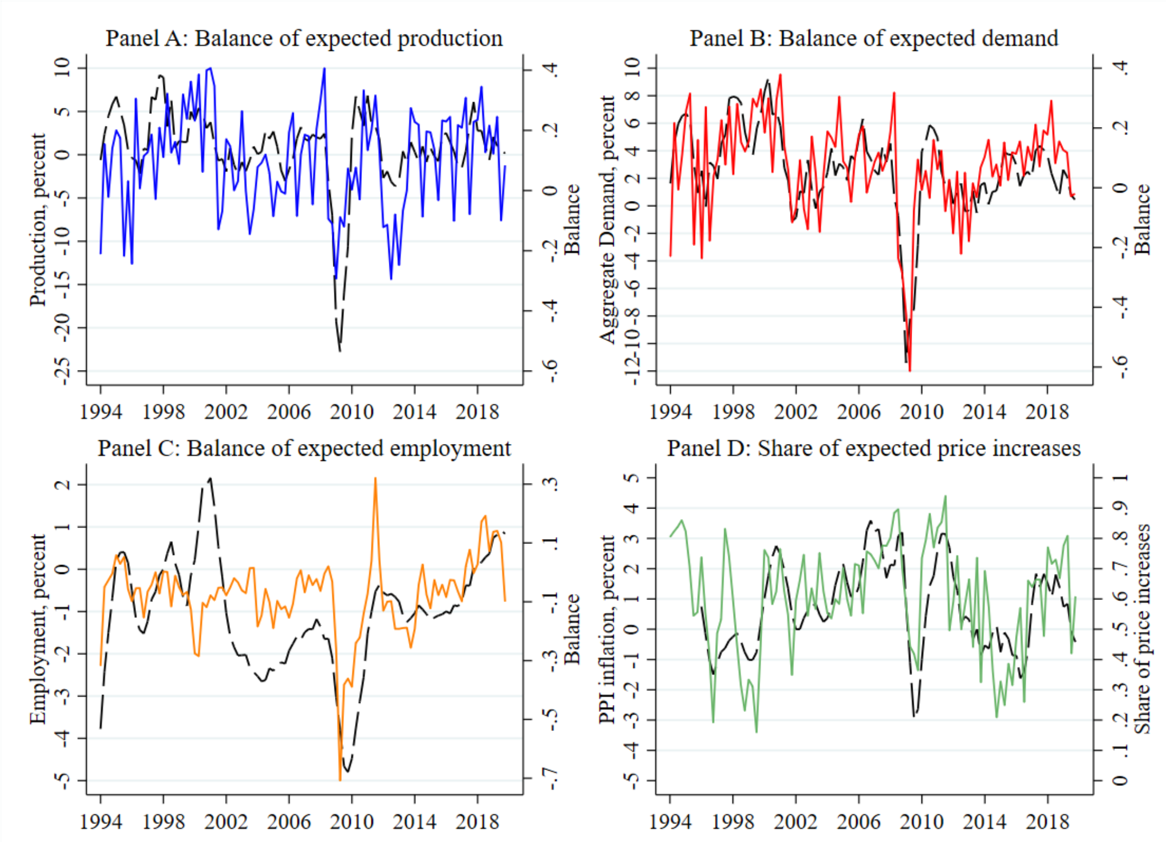
Note: This figure shows the variation of average firm demand forecast error per product*quarter (left panel) and firm*year (right panel).

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



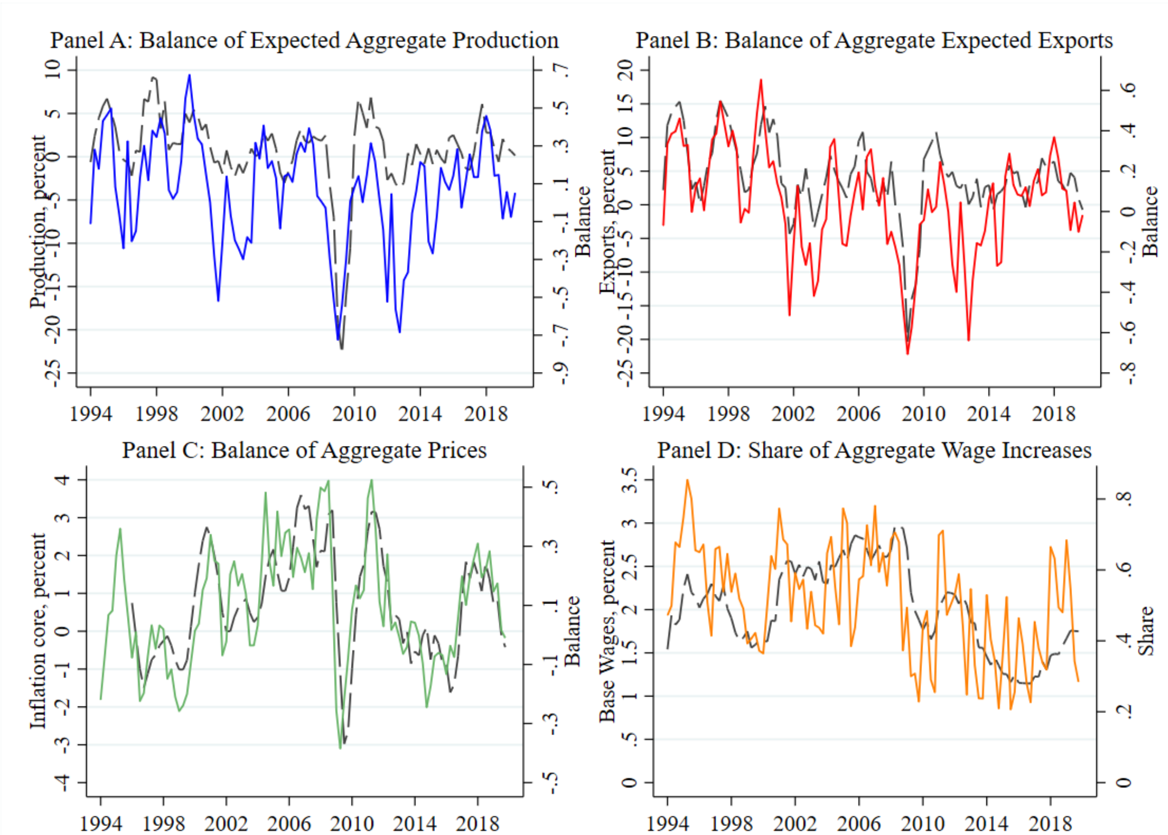
Notes: Panel A plots the difference between the fraction of firms in the survey who report that they increased their production over the previous three months and the fraction of firms reporting a decrease as well as a seasonally adjusted measure of industrial production in France (y-o-y growth rate). Panel B plots the difference between the fraction of firms in the survey who report that their demand increased over the previous three months and 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 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 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 reporting a price increase over the last three months among 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 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.

Table A5: 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/L 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 A6: Descriptive statistics on sector composition

	Nb Sectors	Nb 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 (col. 1) and also statistics on the number of firms by sector for the different levels of sectoral aggregation considered (cols 2-4).

C Consistency

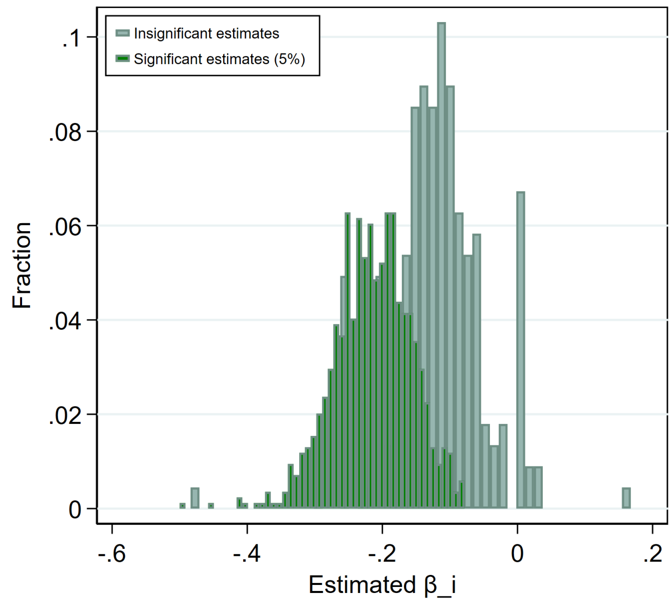
Table A7: Marginal effects on the probability to answer 'increase' to questions on the evolution of its own production, prices and employment

	$PROD^F$	$PRICE^F$	EMP^F
$DMD^F_{i,t}$ increase	0.650***	0.036***	0.104***
	(114.886)	(11.664)	(23.864)
$DMD^F_{i,t}$ decrease	-0.132***	-0.052***	-0.073***
	(-59.440)	(-19.462)	(-45.707)
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 prices will increase is higher by 65 pp. Significance levels: *p<0.10, **p<0.05, ***p<0.01.!

D FIRE deviations

Figure A11: Distribution of estimated individual β_i in Equation (2)



Note: This figure plots the distribution of β_i coefficients estimated from Equation (2) 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 A8: Aggregate forecasts in FIRE regressions

	$DMD^{FE}_{i,t+1}$	$PROD^{FE}_{i,t+1}$	$PRICE^{FE}_{i,t+1}$
$DMD^{FR}_{i,t}$	-0.204***		
	(-132.48)		
$PROD^{FR}_{i,t}$		-0.193***	
		(-125.42)	
$PRICE^{FR}_{i,t}$			-0.180***
			(-100.46)
$PROD^{AGG,FR}_{i,t}$	0.008***	0.007***	0.003**
	(5.10)	(4.34)	(2.27)
$PRICE^{AGG,FR}_{i,t}$	0.004***	0.004**	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: this table presents the results of Equation (2) estimated on the full sample of firms. Forecast errors of different survey variables 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). * p¡0.10 , ** p¡ 0.05, *** p¡ 0.01

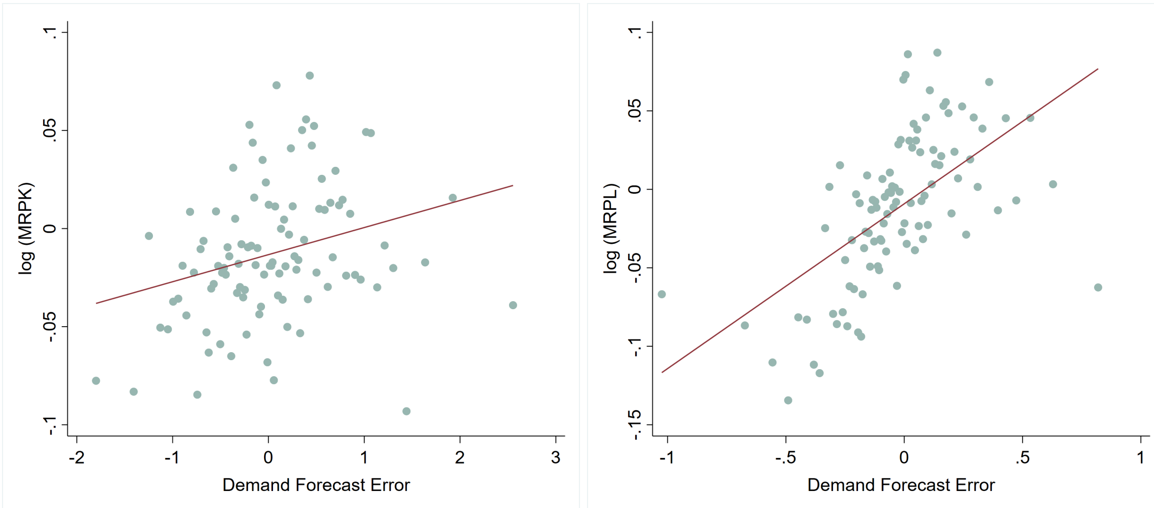
Table A9: Autocorrelation of firms' forecast errors

	$DMD^{FE}_{i,p,t+1}$	$PROD^{FE}_{i,p,t+1}$	$PRICE^{FE}_{i,p,t+1}$
$DMD^{FE}_{i,p,t}$	0.063***		
	(11.79)		
$PROD^{FE}_{i,p,t}$		0.076***	
		(14.09)	
$PRICE^{FE}_{i,p,t}$			-0.007
			(-1.14)
Sector*Year FE	Yes	Yes	Yes
Firm*Prod FE	Yes	Yes	Yes
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<0.05, ***p<0.01; ***p<0.001. 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, $DMD^{FE}_{i,t}$, $PROD^{FE}_{i,t}$ and $PRICE^{FE}_{i,t}$ are the forecast error of a firm i about its own firm demand, production and price, computed as the difference between a forecast made in $t-1$ and the declared realization in t. Forecast errors and forecast revisions are at the product/quarter level.

E 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/L calculated at the firm level (averaging forecast errors and MRPK/L over time).

Table A10: Demand forecast errors and MRPK/L:
Controlling for lagged demand forecast errors and other forecast errors

	$MRPK_{i,t}$			$MRPL_{i,t}$		
$DMD^{FE}_{i,t}$	0.051***	0.049***	0.032***	0.040***	0.039***	0.024***
	(11.62)	(9.29)	(5.31)	(13.68)	(10.55)	(6.40)
$DMD^{FE}_{i,t-1}$		0.040***			0.030***	
		(7.16)			(8.48)	
$PROD^{AGG,FE}_{i,t}$			-0.027***			-0.017***
			(-5.58)			(-5.09)
$PRICE^{AGG,FE}_{i,t}$			-0.004			-0.004
			(-0.71)			(-1.22)
$WAGE^{AGG,FE}_{i,t}$			-0.028***			-0.019***
			(-4.95)			(-4.78)
$PROD^{FE}_{i,t}$			0.021***			0.018***
			(3.53)			(4.95)
$PRICE^{FE}_{i,t}$			0.008			0.010**
			(1.27)			(2.33)
$EMP^{FE}_{i,t}$			0.026***			0.008*
			(4.02)			(1.90)
FE+Controls	Yes	Yes	Yes	Yes	Yes	Yes
N obs	33 191	21 894	28 818	33 325	21 983	28 934
N firms	5 109	3 836	4 661	5 142	3 864	4 686
R^2	0.85	0.86	0.86	0.64	0.65	0.64

Note: Robust t-stats in parentheses clustered at the firm level. **p<0.05, ***p<0.01; ***p<0.001. We report results of OLS regressions relating firm-level MRPK (col 1-3) and MPRL (cols 4-6) to $DMD^{FE}_{i,t}$ the forecast error of a firm *i* about its own firm demand, computed as the difference between a forecast made in $t-1$ and the declared realization in t. Controls included sector*year fixed effects, firm fixed effects and other time-varying firm controls such as age, leverage ratio.... Columns 1 and 4 report our baseline estimates. In Columns 2 and 5, we include one lag of the demand forecast error. In Columns 3 and 6, we include forecast errors for other variables than the firms' own demand like aggregate production, aggregate prices, aggregate wage and also forecast errors on its own production, prices and employment.

Table A11: Robustness: MRPK/L and demand forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: $MRPK_{i,t}$					
	Baseline	Outlier	Prod.	Mono.	Unw.	VA	SD	Small	Price
$DMD_{i,t}^{FE}$	0.054***	0.058***	0.054***	0.055***	0.053***	0.058***	0.076***	0.054***	0.050***
	(11.87)	(11.29)	(11.87)	(11.23)	(12.04)	(11.73)	(11.87)	(11.87)	(10.10)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	33 523	33 908	33 523	28 176	33 523	33 926	33 523	33 523	27 662
N firms	5 143	5 187	5 143	4 485	5 143	5 188	5 143	5 143	4 594
R^2	0.85	0.87	0.85	0.85	0.85	0.87	0.12	0.88	0.85
				Panel B: $MRPL_{i,t}$					
	Baseline	Outlier	Prod.	Mono.	Unw.	VA	SD	Small	Price
$DMD_{i,t}^{FE}$	0.041***	0.047***	0.041***	0.042***	0.040***	0.049***	0.094***	0.041***	0.037***
	(13.54)	(12.17)	(13.53)	(12.94)	(13.50)	(14.49)	(13.54)	(13.54)	(11.36)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	33 648	34 143	33 648	28 311	33 648	33 690	33 648	33 648	27 748
N firms	5 180	5 232	5 180	4 523	5 180	5 187	5 180	5 180	4 622
R^2	0.62	0.62	0.62	0.63	0.62	0.81	-0.02	0.66	0.63

Note: Robust t-statistics in parentheses, clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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/L outliers (defined as values below the 1st percentile and above the 99th percentile of the MRPK/L distributions), Column (3) reports results of a regression controlling for the number of products, Column (4) reports results restricting our sample to mono-product firms, Column (5) reports results where we use unweighted forecast errors, Column (6) reports results where we use value added (excluding taxes) in the MRPK/L calculation, Column (7) reports results of a regression where both MRPK/L and demand forecast errors are normalized by their standard deviation, Column (8) reports results of regression where we exclude small sectors, and Column (9) 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).

Table A12: Asymmetric effect of demand forecast errors

	$MRPK_{i,t}$	$MRPL_{i,t}$
DMD^{FE} optimistic	-0.018***	-0.020***
	(-3.58)	(-5.93)
DMD^{FE} pessimistic	0.027***	0.016***
	(5.44)	(5.15)
FE+Controls	Yes	Yes
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.

Table A13: Local projections - Robustness - Fixed sample + Lagged forecast errors

	t	t+1	t+2	t+3	t+4	t+5	t+6
Panel A: Fixed sample of firms							
				$MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.048***	0.043***	0.037***	0.025***	0.018**	-0.001	-0.007
	(5.83)	(5.58)	(4.57)	(2.80)	(2.00)	(-0.12)	(-0.73)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.89	0.89	0.89	0.88	0.88	0.88	0.88
				$MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.032***	0.029***	0.014***	0.015**	0.006	-0.012*	-0.005
	(6.32)	(5.47)	(2.62)	(2.25)	(1.05)	(-1.81)	(-0.68)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.71	0.71	0.69	0.67	0.65	0.67	0.68
Panel B: One lag of forecast errors as control							
	t	t+1	t+2	t+3	t+4	t+5	t+6
				$MRPK_{i,t}$			
$DMD^{FE}_{i,t}$	0.053***	0.046***	0.019**	0.020**	0.029***	0.024***	0.001
	(9.66)	(7.15)	(2.58)	(2.35)	(2.90)	(2.76)	(0.05)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.85	0.87	0.87	0.86	0.86	0.86	0.85
				$MRPL_{i,t}$			
$DMD^{FE}_{i,t}$	0.041***	0.035***	0.017***	0.017**	0.016**	0.008	0.003
	(10.63)	(7.95)	(3.31)	(2.58)	(2.25)	(1.17)	(0.42)
FE+Con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.64	0.64	0.63	0.63	0.63	0.63	0.63

Note: Robust t-stats in parentheses clustered at the firm level. **p<0.05, ***p<0.01; ***p<0.001. 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 time-varying controls (like age, size...) are also 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.

Table A14: Alternative drivers of MRPL misallocation

	(1)	(2)	(3)	(4)
$DMD^{FE}_{i,t}$	0.041***	0.040***	0.040***	0.040***
	(13.54)	(13.28)	(13.21)	(13.29)
Hiring difficulties		0.022***	0.018***	0.021***
		(5.81)	(4.62)	(5.10)
Hiring difficulties - employees			0.012***	
			(2.89)	
Hiring difficulties - executives				0.004
				(0.83)
Sector*Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N obs	33 648	33 648	33 648	33 648
N firms	5 180	5 180	5 180	5 180
R^2	0.62	0.62	0.62	0.62

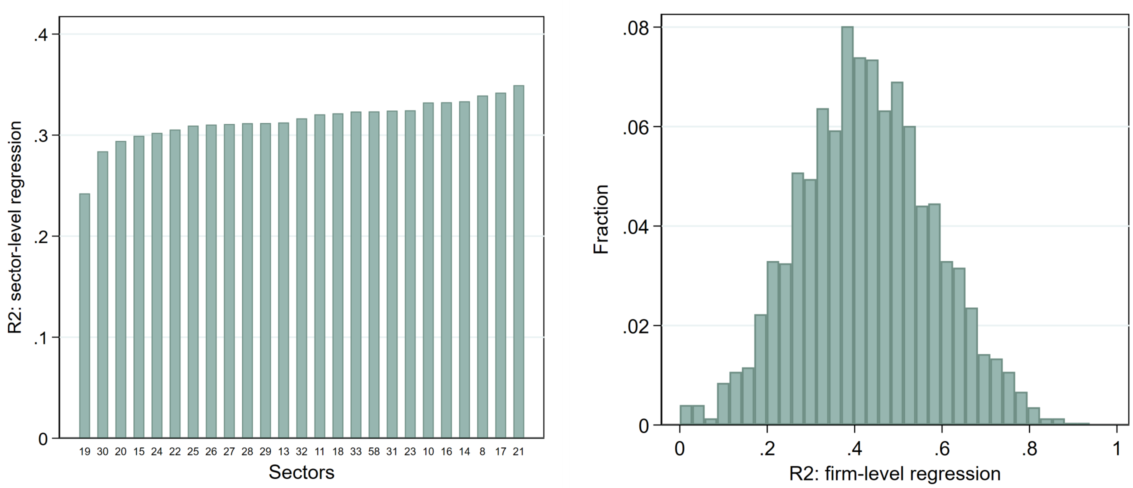
Note: Robust t-stats in parentheses clustered at the firm level. **p<0.05, ***p<0.01; ***p<0.001. The table reports results of regressions linking $MRPL_{i,t}$ to $DMD^{FE}_{i,t}$ the demand forecast error. We also include sector-year and firm fixed effects and some time-varying firm controls. Column 1 reports our baseline results, in Column 2 we include a dummy variable equal to 1 if the firm reports some hiring difficulties in year t, Columns 3 and 4 we include a dummy variable reporting some hiring difficulties by worker category (employees vs managers).

Table A15: 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 adj	0.31	0.33

Note: Robust t-stats in parentheses clustered at the firm level. * $p < 0.05$, ** $p < 0.010$, *** $p < 0.001$.

Figure A13: R^2 of Equation 6 by sectors and by firms



Note: This figure shows the R^2 of Equation 6 estimated by sector (left panel) and by firm (right panel).

Table A16: Robustness of the effect of predictable and idiosyncratic components

	$MRPK_{i,t}$				$MRPL_{i,t}$			
	Baseline	Pooled	Sector	Firm	Baseline	Pooled	Sector	Firm
$DMD_{i,t}^{FE}$	0.048***				0.039***			
	(8.28)				(9.48)			
$DMD_{i,t}^{FE}$ *Pred*		0.036***	0.028**	0.034***		0.022***	0.016**	0.020***
		(3.23)	(2.54)	(4.19)		(2.90)	(2.09)	(3.39)
$DMD_{i,t}^{FE}$ *Shock*		0.036***	0.045**	0.039***		0.035***	0.042***	0.040***
		(4.92)	(6.31)	(5.20)		(7.50)	(9.18)	(8.05)
Sector*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	17 454	17 454	17 453	17 454	17 483	17 483	17 482	17 483
N firms	1 885	1 885	1 885	1 885	1 897	1 897	1 897	1 897
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.