Business Uncertainty in Developing and Emerging Economies*

Edgar Avalos* Jose Maria Barrero** Elwyn Davies*
Leonardo Iacovone*** Jesica Torres*

April 2025

Abstract

How much does managerial uncertainty about cash-flow drivers matter for aggregate investment? Using surveys of over 31,000 managers across 41 countries, we establish two new facts. (1) Subjective uncertainty about own-firm sales and realized sales volatility both decline with GDP per capita. (2) Managers underestimate volatility everywhere (they are *overprecise*), but more so in low-volatility rich countries. Calibrating a heterogeneous-firm model to match our facts, we show they rationalize the empirical upward-sloping relationship between aggregate capital-output ratios and GDP per capita. Overprecision accounts for half of the gradient, suggesting managerial belief distortions might be a first-order driver of cross-country investment.

JEL classification: D84, G31, G32, E22, E23, O11, D25

Keywords: Managers, uncertainty, volatility, overprecision, capital-output ratios, aggregate TFP, real options

*We thank World Bank colleagues and numerous organizations listed in Apedo-Amah et al. (2020) who supported the collection of the survey data. For helpful comments, we thank Rudi Bachmann (discussant), Felipe Brugués, Nick Bloom, Michael Boutros, Steve Davis, Jan Eberly, John Graham, Pete Klenow, Aart C. Kraay, Daniel Lederman, Brent Meyer (discussant), Francisco Perez-Gonzalez, Francisco Parro, Cian Ruane, Alejandro Vicondoa (discussant), Andrés Zambrano and participants at SITE, ITAM Finance Conference, AEA San Francisco, AFA San Antonio, ifo Conference on Macro and Survey Data, NYFED Conference on Expectations Surveys, IEF Workshop Santiago, the World Bank, and various seminars. Barrero thanks Asociación Mexicana de Cultura A.C. for financial support. Diego Álvarez and Santiago Cordero provided excellent research assistance. The views expressed in this article are solely those of the authors and do not necessarily reflect the views of the World Bank, its Executive Directors, or the countries they represent.

*The World Bank. **Instituto Tecnológico Autónomo de México (ITAM), corresponding author: jose.barrero@itam.mx. ***The World Bank and the Hertie School.

1. Introduction

How much do cross-country differences in business uncertainty matter for firm-level investment decisions, and ultimately for aggregate outcomes? A long-standing literature links high economic uncertainty to low investment, usually because uncertain managers prefer to wait rather than take up investment opportunities or reallocate their capital (see, e.g., Bernanke, 1983, Abel and Eberly, 1996, and Baker et al., 2024). Underlying this logic is the question of how managers *perceive* cash-flow risk in high- versus low-volatility settings. Yet, there is limited data on subjective uncertainty from systematically different environments. And mounting evidence suggests that widely used measures of ex-post volatility do not accurately reflect manager perceptions of uncertainty (e.g., see Ben-David et al., 2013; Boutros et al., 2020; Barrero, 2022). That leaves open the question: can subjective uncertainty about own-firm cash flows, through its impact on capital budgeting, explain cross-country differences in aggregate investment, such as capital-output ratios?

We address these questions using a new survey of over 31,000 managers across 41 countries. We measure managers' subjective uncertainty about future own-firm sales and estimate realized sales volatility from their absolute forecast errors. The data reveal systematic differences in uncertainty and volatility across countries. We also establish that managers are *overprecise*: they systematically underestimate the amount of volatility their firms are exposed to, and we show how that differs across countries. Then we link these facts to cross-country differences in aggregate investment. We build a dynamic model in which manager perceptions of uncertainty and realized volatility both matter for outcomes. Calibrating the model to match our facts, we show that managerial overprecision and cross-country differences in volatility can explain long-standing patterns in capital-output ratios across rich and poor countries.

Our data come from the World Bank's Business Pulse and Enterprise Surveys (BPS and ES), fielded in dozens of countries across Eastern Europe, Asia, Africa, and Latin America. The surveys interview business managers and elicit subjective probability distributions for future own-firm sales at a six-month horizon. Adapting the methodology of Altig et al. (2022), those distributions have three support points: a central, an optimistic, and a pessimistic scenario. We obtain managerial forecasts or expectations from their first moments and measure subjective uncertainty from their mean absolute deviations. In a subset of countries we also track firm outcomes across time and construct absolute forecast errors to measure realized volatility. We focus on managerial sales projections because they are central to decision-making, as noted by Graham (2022). The cross-country dimension of our data (similar to Weber et al., 2025) helps us go further than other work on business

surveys within advanced economies (e.g., Bloom et al., 2021; Bachmann et al., 2024).

We validate the data by replicating key results from that prior literature. We show managerial forecasts predict future sales, and that managers who report more uncertainty go on to make larger absolute forecast errors. They tend to report high uncertainty in volatile situations; for example, after large (positive or negative) shifts in sales. Hiring decisions and plans also line up with expectations and uncertainty, consistent with experimental evidence by Kumar, Gorodnichenko, and Coibion (2023).

Our paper makes two key contributions. First, we document new facts about business uncertainty and volatility across countries. Both decline with GDP per capita, as Figure 1a shows. That means managers in poor countries foresee more variation across future sales scenarios, and they make larger absolute forecast errors than rich-country managers. These relationships hold for country-level averages, and when we regress firm-level uncertainty and absolute forecast errors on GDP per capita and a wide range of controls for firm and macro conditions – including for the business-cycle. In Figure 1 and elsewhere we also bring in data from the Atlanta Fed Survey of Business Uncertainty to show the pattern extends to the United States before and after the pandemic. By contrast, we find little evidence that expectations or subjective skewness differ systematically across countries.

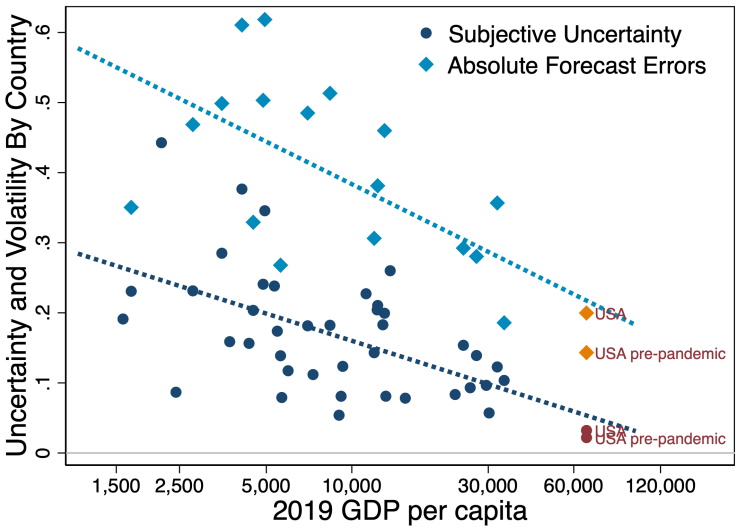
Our result that firm-level sales are harder to forecast in poor countries, and managers recognize it, builds on prior work. For example Haltiwanger et al. (2008) and Asker et al. (2014) find more variability in firm employment and productivity in poor countries. We go further by showing that variability reaches managers' viewpoints and information sets. It reflects *unforecastable* risk that raises managerial uncertainty, not just high measurement error. Our results also echo findings by Ayerst et al. (2024) showing firm-level productivity is more dispersed in middle- than high-income countries.

More fundamentally, we find managers systematically underestimate sales volatility; namely, they are *overprecise*.[1] Figure 1b plots average absolute forecast errors (i.e., realized volatility) by country against subjective uncertainty. If managers had rational expectations and there were no large common shocks, we would expect the data to line up along the 45-degree line. Instead, absolute forecast errors are larger than uncertainty with 95% confidence in every country. A similar, statistically-significant relationship holds at the country-sector level, with absolute forecast errors exceeding uncertainty in 85 out of

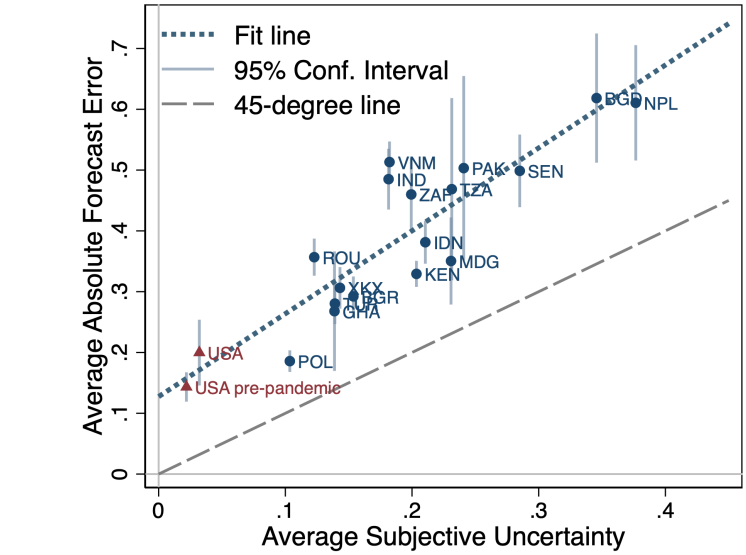
[1]Other authors refer to this phenomenon as *overconfidence* because it is equivalent to the manager overestimating their ability to make accurate forecasts, or *miscalibration* to emphasize the discrepancy between the subjective stochastic process that managers use and the econometrician's. We prefer the term *overprecision*, because we find it more descriptive and because different studies use *overconfidence* in different ways. For example, overconfidence in Malmendier and Tate (2005) could be interpreted as a combination of *overoptimism* and overprecision.

Figure 1: **Two New Facts About Business Uncertainty Across Countries**

(a) **Uncertainty and Volatility Decline with GDP per Capita**



(b) **Managers are Overprecise: Absolute Forecast Errors Exceed Uncertainty in Every Country**



Fit line: Absolute Forecast Error = .1 + 1.4 * Uncertainty

Notes: Figure 1a plots employment-weighted average subjective uncertainty and average volatility (i.e., absolute forecast errors) in each country (averaging across survey waves for the same country) against 2019 PPP GDP per capita (in 2019 US dollars). Figure 1b plots employment-weighted average absolute forecast errors (volatility) by country against average subjective uncertainty. Uncertainty and forecast error data are from the World Bank Business Pulse and Enterprise Surveys, and the Atlanta Fed Survey of Business Uncertainty for the US. The US data pool SBU waves from June 2020 to March 2022, and October 2014 to May 2019 for the unlabeled and pre-pandemic data points, respectively.

89 individual country-sectors. Unforecastable macro shocks cannot explain away these patterns: they only account for a modest fraction of mean squared forecast errors. Instead, managers seem to systematically underestimate own-firm sales risk.

Our data and setting position us uniquely well to establish managerial overprecision as a widespread phenomenon in rich and poor countries. We also show it is more severe in *percentage* terms in rich ones, where managers seem to tune out a larger share of idiosyncratic sales risks. We can see this pattern in Figures 1a and 1b. Both show a roughly constant gap between uncertainty and absolute forecast errors as we move along the horizontal axis. The gap or underestimate, thus, accounts for a larger share of total volatility in richer, lower-volatility countries. That is counter-intuitive, since rich-country managers are probably more educated and sophisticated. This cross-country evidence adds to prior work on overprecision in the United States and over time. For example, Boutros et al. (2020) find persistent overprecision among US managers and Bianchi et al. (2024) study its effects over the business cycle. Lochstoer and Muir (2022) also show that investor beliefs underreact to spikes in market volatility.

The second major contribution of our paper is to quantify the link from cross-country differences in uncertainty, volatility, and overprecision to aggregate investment and output. To do so, we build a heterogeneous-firm dynamic model with partially irreversible investment and allow for a disconnect between subjective uncertainty and realized volatility. We follow Barrero (2022) in assuming managers use a subjective stochastic process to forecast firm profitability, letting its conditional volatility differ from that of the objective profitability process. Thus, investment decisions depend both on managers' subjective uncertainty and on the realized volatility of profitability shocks.

We trace out the importance of our facts through a series of counterfactual calibrations of the model. Calibrated to match the amount of uncertainty and volatility in rich and poor countries, as well as GDP-per-capita gaps, the model delivers an upward sloping relation between aggregate capital-output ratios and GDP per capita. In fact, the gradient matches corresponding empirical estimates in Penn World Table (Feenstra et al., 2015) data for our sample of countries and more broadly. We do not target any cross-country investment outcomes in our calibration, so this is effectively an overidentifying test of the model.

The model's ability to fit capital-output ratios, however, depends crucially on whether we calibrate it to our empirical facts. The relationship breaks down when we fail to target some or all of them in the calibration. If we ignore the evidence on subjective uncertainty and overprecision, the model still yields a positive relation between capital-output ratios and GDP per capita. But the slope is only half as large as in the full calibration and in the data. If we additionally ignore cross-country differences in volatility, we obtain no

gradient in capital-output ratios at all. That suggests overprecision and managerial beliefs are first-order drivers of firm-level and aggregate investment in the model, accounting for half of the empirical pattern. Differences in volatility account for the other half.

There are two reasons why volatility and overprecision drive investment in our calibrated model. First, firm value and investment are convex functions of profitability in our model, just as in many other standard models of investment. Combined with high volatility, that convexity yields investment opportunities and higher GDP per capita via a classic Oi-Hartman-Abel effect (see Oi, 1961, Hartman, 1972, and Abel, 1983). The same logic explains the positive link between (unlevered) asset volatility and investment documented by Chang et al. (2024). But high volatility is a feature of poor countries that struggle to invest, not rich ones. Our calibrations resolve that tension by giving volatile poor countries low TFP residuals, restraining investment and yielding low capital-output ratios.

Second, overprecision distorts managerial investment decisions in ways that also lead to low capital-output ratios, especially in volatile poor countries. When managers are overprecise, they underestimate sales risk and therefore undervalue the real options that let them delay investment decisions (see, e.g., Abel and Eberly, 1996; Abel et al., 1996; Bloom et al., 2007; Bachmann and Bayer, 2013). Overprecise managers, thus, reallocate capital away from unproductive firms very swiftly. And, because they undervalue the firm and its growth options, they also underinvest in response to high profitability shocks. The result is lower investment and capital-output ratios in economies with overprecise managers. These effects become stronger with volatility, so overprecision depresses aggregate capital-output ratios disproportionately in poorer, more volatile countries.

Our model's success at matching cross-country capital-output ratios does not come for free. We achieve it by allowing for wider TFP gaps between rich and poor countries. That suggests volatility and overprecision interact with other frictions that deter investment in poor countries. Those might involve financial factors, like high costs of capital due to risk premiums or impatience (e.g., see David et al., 2014 and Falk et al., 2018), or reallocation frictions (e.g. Eisfeldt and Rampini, 2006). Vereshchagina (2022) suggests financing constraints deter poor-country managers from investing in their firms' productivity, especially under high volatility. Limits to delegation (Akcigit et al., 2021) or firm-level distortions (Ayerst et al., 2024) might be involved too. Our data and model, ultimately, say that managerial perceptions of uncertainty are first-order determinants of investment at the firm and macro levels, and they are complementary to those other real and financial frictions.

In the rest of our paper, we describe our data and methodology and validate our measures of expectations and uncertainty (Section 2). Then, we document our new facts about uncertainty and volatility across countries (Section 3). We build a dynamic, heterogeneous-

firm model (Section 4) and quantify the implications of our facts by bringing the model to the data (Section 5). In Section 6 we discuss our results and conclude in Section 7.

2. Surveying business uncertainty in developing and emerging economies

This section introduces the World Bank's Business Pulse and Enterprise Surveys that we use to measure expectations and uncertainty about future own-firm sales, as well as realized sales volatility.

2.1 Survey methodology

The World Bank Group's Business Pulse Survey (BPS) and Enterprise Survey (ES) interviewed managers in dozens of countries between April 2020 and March 2022, asking them about firm operations, sales, employment, and performance after the onset of the pandemic. In most countries, the surveys were conducted in partnership with local statistical agencies, government departments, or business associations. Enumerators collected the data during telephone interviews with business owners and top managers in the local language. In our data 68% of respondents are the firm's owner, CEO, or CFO; 19% are the top manager; 6% are the accountant or chief in-house counsel; and the remaining 7% have other positions. Interested readers can refer to Apedo-Amah et al. (2020) for more details.

Our dataset covers 41 countries from all of the regions served by the World Bank.[2] The lowest-income countries in our data are Malawi, Madagascar, Sierra Leone, and Afghanistan with 2019 PPP GDP per capita under $2,500. At the high end, we have Malaysia, Croatia, Romania, and Poland, some of which are above $30,000. In 18 countries, the BPS collected follow-up survey waves that re-interviewed many of the original respondents, tracking those firms' performance over time. In the remaining 23 countries we have data from a single wave (i.e., a single cross-section). Altogether, our dataset includes 67 country-wave instances. Table B1 in the appendix shows the full list of countries and a timeline of when each survey wave took place. Table B2 shows the number of panel observations in countries with multiple waves.

The firms in our dataset are primarily from manufacturing and services sectors, and range in size from small (5 to 19 workers) to medium (19 to 99 workers) and large (100 or more workers).[3] We exclude firms in the education and health sectors due to differences

[2] In 36 of the 41 countries the data come from the BPS. In Guatemala, Honduras, Nicaragua, El Salvador, and Mongolia, the surveys were follow-ups to an earlier Enterprise Survey (ES) and used the same questionnaire as the global BPS.

[3] Managers of micro firms (with fewer than 5 workers) did not get the key questions we use to measure expectations, uncertainty, and absolute forecast errors, so we exclude them from our analyses. In some countries, the BPS did not include those key questions at all, so our dataset does not cover some countries

in coverage across countries, and because governments often play a large role in those industries. We also exclude firms that closed permanently by the time of the interview. Table B3 shows our dataset's coverage across size groups and sectors by country.

The sampling frame in most countries comes from census listings, business registers, or other administrative sources available to the World Bank and the local partners. Our data therefore focuses on businesses attached to the formal economy. But the surveys ask about total (formal and informal) sales and employment, covering business activity broadly even where the informal economy is large.

2.2 Measuring expectations, uncertainty, and ex-post volatility

We measure managerial expectations and uncertainty using a survey module that elicits subjective probability distributions about own-firm sales at a six-month look-ahead horizon (see, e.g., Manski, 2004 and Altig et al. (2022)). We focus on sales projections because they are the top-line focus of managerial capital budgeting and planning, as Graham (2022) argues. Table 1 shows English-language versions of the underlying survey questions, which adapt the methodology developed by Altig et al. (2022). First, interviewers ask managers to project the firm's sales looking six months ahead under a central scenario (expressed as a percentage change from the same period in the prior year) and a probability for that outcome. Then interviewers ask them to consider an optimistic and a pessimistic scenario, asking for a sales outcome and probability for each. This three-point approach is highly consistent with capital budgeting practice, for example as taught in business schools. A complete response yields a subjective distribution with three support points $\{g_i\}_{i=1}^3$ and three corresponding probabilities $\{p_i\}_{i=1}^3$, where i indexes the three (pessimistic, central, and optimistic) scenarios. We express respondent estimates of six-months-ahead sales in each scenario (g_i) as an arc-change from the prior year.[4] This choice follows the literature on business dynamics, which favors arc-changes for their symmetry around zero, approximation of log-changes, and easy aggregation (see, e.g., Davis et al., 1998).

We measure each manager's sales forecast or expectation with the first moment of their subjective distribution for future sales:

$$\text{Expectation} = \sum_{i=1}^{3} \frac{p_i}{100} g_i. \tag{1}$$

that fielded the broader survey.

[4]Assuming the respondent's projection in scenario i, h_i represents a proportional change (where $h_i = .01$ means a 1% increase), the arc-change is $g = {}^{2h_i}/_{(h_i+2)}$. To see why, define $h_i \in [-1, \infty)$ as a proportional change in x: $h_i = (x_i' - x)/x$ where x_i' is the future value of x in scenario i. The arc-change, defined as $g \equiv (x_i' - x)/(0.5(x_i' + x)) = 2h_i/(h_i + 2)$.

Table 1: **Expectations and Uncertainty Survey Module**

Question	Response options
1. Regular (most likely) scenario	
Q1a. Looking ahead to the next 6 months, do you expect that your sales will increase, decrease, or remain the same, compared to the same period last year?	Increase / Decrease / Remain the same
If *Increase*: **Q1b.** Increase by how much?	Percentage change
If *Decrease*: **Q1c.** Decrease by how much?	Percentage change
Q1d. On a scale of 0 to 100, what is the chance (probability) you believe this will happen?	Probability (0-100)
Prompt: As you know, sometimes businesses don't go as we expect. Given that businesses can go better or worse, let us talk about these possible alternative situations:	
2. Optimistic scenario	
Q2a. In a more optimistic (better) scenario, do you expect that your sales for the next 6 months will increase, decrease, or remain the same, compared to the same period last year?	Increase / Decrease / Remain the same
If *Increase*: **Q2b.** Increase by how much?	Percentage change
If *Decrease*: **Q2c.** Decrease by how much?	Percentage change
Q2d. On a scale of 0 to 100, what is the chance (probability) you believe this will happen?	Probability (0-100)
3. Pessimistic scenario	
Q3a. In a more pessimistic (worse) scenario, do you expect that your sales for the next 6 months will increase, decrease, or remain the same, compared to the same period last year?	Increase / Decrease / Remain the same
If *Increase*: **Q3b.** Increase by how much?	Percentage change
If *Decrease*: **Q3c.** Decrease by how much?	Percentage change
Q3d. On a scale of 0 to 100, what is the chance (probability) you believe this will happen?	Probability (0-100)

Notes: This table shows English-language versions of the questions that appear in the expectations and uncertainty module of the 2020-2022 World Bank Group Business Pulse and Enterprise Surveys. In each country, interviewers elicited these questions over the phone in the local language. See Apedo-Amah et al. (2020) for the full questionnaire.

In turn, we measure subjective uncertainty with the mean absolute deviation of the distribution:

$$\text{Uncertainty} = \sum_{i=1}^{3} \frac{p_i}{100} \cdot |g_i - \text{Expectation}|. \tag{2}$$

We use mean absolute deviations to make our measures of uncertainty analogous to

absolute forecast errors, which we can construct with data on realized sales g':

$$\text{Absolute Forecast Error} = |g' - \text{Expectation}|. \tag{3}$$

We can construct those absolute errors in the 18 countries where the BPS and ES ran follow-up survey waves and reached many of the original participants. In those follow-up interviews, managers report the firm's recent sales level as a percent change from the same reference period used in the original interview.[5] That means those sales outcomes are comparable to the expectations we compute from the original interview, and we can use them to construct forecast errors.

We interpret average absolute forecast errors within a country or country-sector as measures of realized (idiosyncratic) sales volatility. Indeed, absolute forecast errors measure the magnitude of shocks that managers cannot forecast, in the same spirit as the uncertainty/volatility indices developed by Jurado et al. (2015). Throughout the paper we refer to average absolute forecast errors and (realized, idiosyncratic) volatility interchangeably.

Our raw data include almost 40,800 subjective distribution observations provided by 31,219 distinct managers. Almost 24,000 managers participated in the survey once and a further 7,300 participated twice or more. To compute expectations and uncertainty from those responses we need them to satisfy the following: (1) the probability distribution must have at least two distinct support points for potential future sales; (2) the sum of the probabilities must equal 100; and (3) at least two support points must have positive probability mass.[6] Where necessary, we make minor imputations to the respondents'probability vector to obtain such a distribution. See Section B.1 in the internet appendix for more details. We would prefer not to have to make these imputations, but our results change little when we drop observations with imputed probability vectors, as we discuss in Section 3. Indeed, Altig et al. (2022) show that measures of expectations and uncertainty rely more heavily on the support points, which we do not impute, than on the probabilities.

Our analysis dataset, after running the cleaning and imputation procedures, includes 28,612 subjective distribution observations from 41 countries. Among them, 8,550 (30% of

[5]The exact wording of the realized sales question is "Comparing this establishment's sales for the last 30 days before this interview with the same period last year, did the sales increase/decrease/or remain the same? Increased/decreased by how much (in percentage terms)?" See Apedo-Amah et al. (2020) for the full questionnaire. Follow-up interviews were sometimes held somewhat earlier or later than six months after the original interview. As with the future sales outcomes in the expected distribution, we express realized sales levels as arc-changes from the reference period.

[6]The likelihood that a firm is unable to provide a non-degenerate, usable subjective distribution declines with firm size within a country, wave, and sector, as Figure A.10 in the appendix shows. Bloom et al. (2021) similarly show how larger and better-managed manufacturing plants are more likely provide non-degenerate distributions with probabilities that add up to 100.

the final sample) have a rescaled or imputed probability vector. Table B4 shows the number of subjective distributions in the raw data and the final sample, grouping country-waves by the calendar quarter when data collection ended. Our survey efforts are successful when compared with other large-scale efforts to elicit subjective probability distributions. For example, Bloom et al. (2021) obtain usable subjective distributions from 85% of US manufacturing plants responding to a mandatory US Census survey. Thus, we contribute to a growing literature on business expectations surveys reviewed by Born, Enders, Müller, and Niemann (2023).[7] Our paper stands out within this literature by providing data on expectations and uncertainty from dozens of developing and emerging economies.

2.3 Summary statistics about expectations and uncertainty

Panel (a) of Table 2 reports unweighted means and standard deviations for each of the three (optimistic, central, pessimistic) support points and their corresponding subjective probabilities. They show how our survey methodology accommodates vast cross-firm heterogeneity, by giving respondents five degrees of freedom to specify the distribution of future sales outcomes (3 support points plus 3 probabilities adding to 100). Average sales projections range from -45% for the pessimistic scenario to $+16\%$ for the optimistic one, with wide standard deviations, even within country-waves. The average probability assigned to the central scenario is about 40%, similar to the average for the middle support point in Altig et al. (2022), and near 30% for the optimistic and pessimistic scenarios. Again, the standard deviations around those averages are wide.

Panel (b) of Table 2 reports employment-weighted means and standard deviations of our measures of sales expectations, uncertainty, and forecast errors. It also reveals vast cross-firm heterogeneity in expectations and uncertainty. While the average expectation calls for a 6% drop in sales over the next six months, the standard deviation around that average is 35%. Average uncertainty is 18%, and the average absolute forecast error is 43%, each with standard deviations about as large in the full sample and within country-waves. The average forecast error is markedly negative due to the pandemic setting (and driven by large errors in Bangladesh, Nepa, and Sierra Leone), but there is a wide standard deviation around that average. We report employment-weighted statistics here and in most of our empirical work to better reflect aggregate activity. That said, our key results are not sensitive to weighting.[8]

[7] See also Guiso and Parigi (1999); Bachmann et al. (2013); Bachmann et al. (2024); Altig et al. (2022); Coibion et al. (2020); Ma et al. (2020); Andrade et al. (2021); and Meyer, Parker, and Sheng (2021), among others. A separate literature focuses on households. For example, Koşar and Van der Klaauw (2023) use density forecasts to examine perceptions of future earnings and employment risk.

[8] The weight for each firm is the total number of full-time and part-time workers they report in the survey,

Table 2: **Summary Statistics: Subjective Distributions and Their Moments**

(a) **Support Points for Six-Months Ahead Sales and Probabilities**

	Scenario	Mean	SD	SD Within Country-Wave
Support point for future sales	Pessimistic	-0.45	0.56	0.48
	Central	-0.08	0.42	0.37
	Optimistic	0.16	0.30	0.27
Probability	Pessimistic	27.3	16.1	15.2
	Central	38.7	16.8	15.7
	Optimistic	34.1	15.8	15.0

(b) **Expectations and Uncertainty Measures**

	Mean	SD	SD Within Country-Wave
Expected six-months-ahead sales	-0.06	0.35	0.34
Subjective uncertainty of six-months-ahead sales	0.18	0.18	0.17
Forecast error, six-months-ahead sales	-0.16	0.58	0.57
Absolute forecast error, six-months-ahead sales	0.43	0.42	0.39

Notes: Panel (a) reports unweighted means and standard deviations for the support points and probabilities,of the three-point subjective distributions that managers report in the World Bank Business Pulse and Enterprise Surveys. Panel (b) reports the employment-weighted mean and standard deviation of our measures of six-months-ahead sales expectations and subjective uncertainty (i.e., the first and second moments of the three-point distributions.) The sample includes 28,612 survey responses in our analysis sample for which we can obtain first and second moments, and 4,868 forecast error observations with expectations and realized sales reported in a follow-up interview. See the main text for an overview of our cleaning procedures. Sales outcomes in each scenario are for a six-month look-ahead period, and sales levels are expressed as arc-changes relative to the same period in the prior year.

2.4 Validating our measures of expectations and uncertainty

We validate our measures of expectations, uncertainty, and absolute forecast errors by replicating key results from earlier surveys of managers that focus on future own-firm outcomes: namely, Altig et al. (2022), Bloom et al. (2021), and Bachmann et al. (2024). While these are not novel results, we report them to document the reliability of our data and our key empirical contribution in Section 3.

scaling the weights so they add up to 1 in a given country-wave. When our analysis exploits the panel dimension of our data, we use employment at the time of the second wave and scale the weights so they add up to 1 within each country rather than each country-wave, to avoid giving countries with third waves mechanically more weight in those results.

Expectations predict future sales, and uncertainty predicts realized volatility

Our measures of expectations and uncertainty contain information about future outcomes. There is a positive and significant relationship between managers' sales expectations in the initial interview and the sales outcomes they report in follow-up interviews, as the binned scatter plot in panel (a) of Figure 2 shows. This result is consistent with Altig et al. (2022), Barrero (2022), and Bloom et al. (2021) and it validates our view of managerial expectations as forecasts of subsequent sales.

We also find a positive relationship between subjective uncertainty and absolute forecast errors, shown in panel (b) of Figure 2. Managers who express high uncertainty ex-ante make forecasts that are less accurate ex-post. This is the same relationship uncovered by Altig et al. (2022) and Barrero (2022). It suggests that managers express higher uncertainty when they foresee their firm being subject to higher volatility.

Uncertainty reflects shifts in the business environment

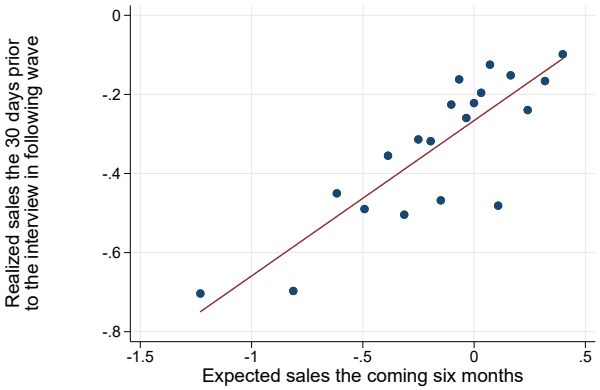
Managers are more uncertain after seeing large recent shifts in their firm's sales. Panel (c) of Figure 2 shows this pattern using an employment-weighted binned scatter plot of subjective uncertainty against realized sales in the 30 days prior to the interview. Independent regressions of uncertainty on recent sales on either side of zero estimate statistically and economically significant relationships (as the estimates below the figure show). This result replicates similar findings from surveys of managers in Germany (see Bachmann et al., 2024) and the United States (see Altig et al., 2022 and Bloom et al., 2021). It also confirms that our measures of subjective uncertainty reflect instability in the firm's environment. We report three additional tests of that principle in appendix Figure A.1.

Expectations and uncertainty correlate with employment outcomes and plans

The final test of the validity of our data links our measures of expectations and uncertainty to employment outcomes and plans in Table A.1. Thus, our measures of expectations and uncertainty are consistent with managers' current or planned actions. We regress changes in employment in the 30 days before the survey on expectations and uncertainty about six-months-ahead sales. Managers who forecast higher sales report higher recent employment growth, and those who express high uncertainty report lower employment growth. High sales forecasts are accompanied high employment forecasts in the subset of the data where we can measure employment plans using questions about future employment that

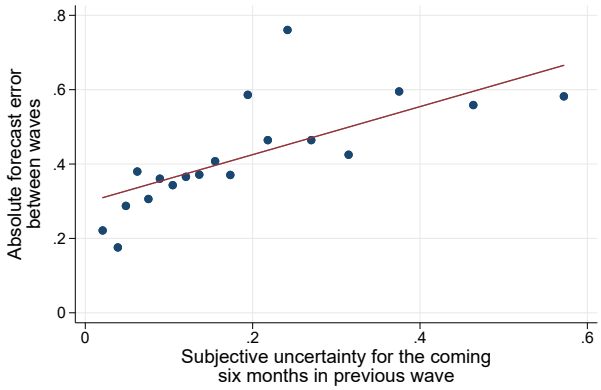
Figure 2: **Validating Our Measures of Expectations and Uncertainty**

(a) **Expectations Predict Future Sales**



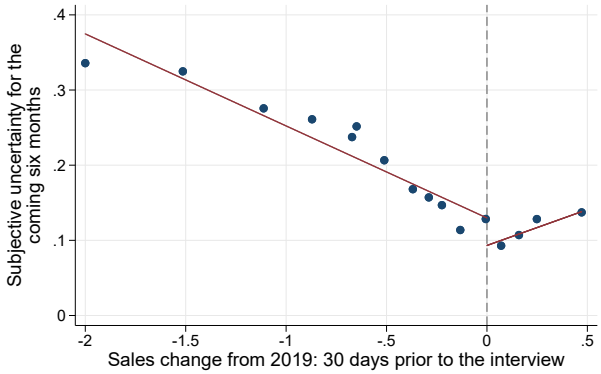
No. of observations: 4868.
Coefficient: 0.39 with standard error of 0.069.

(b) **Uncertainty Predicts Absolute Forecast Errors**



No. of observations: 4868.
Coefficient: 0.65 with standard error of 0.095.

(c) **Uncertainty is V-shaped in Sales Shifts**



No. of observations: 3626.
Coefficient of the left-side: -0.12 with standard error of 0.005.
Coefficient of the right-side: 0.10 with standard error of 0.024.

Notes: Panel (a) shows a binned scatter plot of realized sales in the 30 days prior to the follow-up interview against sales forecasts as of the initial interview. Panel (b) shows a binned scatter plot of absolute forecast errors against subjective uncertainty about six-months-ahead sales. Panel (c) shows a binned scatter plot of subjective uncertainty against sales shocks recorded in the 30 days prior to the interview. Realized and expected sales are both expressed as arc-changes from the same period in the prior year. The sample for panel (c) includes businesses from all countries and waves. Panels (a) and (b) include firm-level observations with a follow-up interview. All estimates and plots are employment-weighted. The reported statistics below each figure are from the least squares regression in the underlying microdata and the corresponding robust standard error clustered by country-sector.

resemble those about future sales in Table 1.[9] We also link uncertainty about future sales to uncertainty about future employment. So, managers who anticipate a wide rage of sales outcomes in the next six months also anticipate a wide range of employment outcomes.

[9]Initial waves of the survey, conducted in a handful of countries included these questions about the distribution of future employment.

3. Two new facts about business uncertainty and volatility across countries

We establish two new facts about manager perceptions of own-firm sales uncertainty and realized sales volatility, shown in Figure 1.

1. Subjective uncertainty about future sales and realized sales volatility (measured by average absolute forecast errors) decline with GDP per capita, as Figure 1a shows.

2. Managers underestimate sales volatility everywhere: they are *overprecise*. In every country where we can measure average uncertainty and absolute forecast errors, Figure 1b shows average absolute forecast errors are larger with at least 95% confidence. (All points are above the 45-degree line.) Moreover, we show the degree of overprecision differs across countries. Rich-country managers, who operate in low-volatility environments, underestimate volatility by a greater *percentage*.

3.1 Uncertainty and volatility decline with GDP per capita

Managers in poor countries express higher uncertainty when they provide subjective distributions for future sales. Their firms are also exposed to larger unforecastable (idiosyncratic) shocks, leading to larger forecast errors. We can see both of these patterns in Figure 1a, which computes employment-weighted average uncertainty and volatility (i.e., absolute forecast errors) by country and plots them against 2019 PPP-adjusted GDP per capita (expressed in 2019 US dollars).[10] In both cases there is a negative relationship, as confirmed by linear regressions estimated on the cross-country data.

Figure 1a includes two additional data points for the US before and after the pandemic, taken from the Atlanta Fed's Survey of Business Uncertainty (SBU) (see Altig et al., 2022). The SBU collects subjective distributions about four-quarters-ahead sales growth that yield measures of uncertainty and absolute forecast errors like those in the World Bank data. The pre-pandemic USA point covers October 2014 to May 2019, while the unlabeled USA point uses data from June 2020 to March 2022, spanning the sample period of our World Bank surveys. Despite modest differences between the two datasets, both of the USA data points line up with the broader cross-country evidence.

Tables 3 and 4 use firm-level microdata regressions to show that managers in poor countries are systematically more uncertain and make systematically larger forecast errors

[10]Figure 1a and many of our country-level analyses below drop data from Sierra Leone because it has much larger realized volatility than other countries. Figure A.3 also shows the average forecast bias in Sierra Leone is far larger than in other countries. To avoid drawing inferences from that outlier and out of concerns for data-quality, we exclude it from our main country-level sample.

than their peers in rich countries. We regress firm-level uncertainty and absolute forecast errors, respectively, on log(GDP per capita) and a range of micro and macro variables. We include those other variable to show that the headline relationship with GDP per capita is not easily explained away by sampling differences across countries, or swamped by within-country heterogeneity in uncertainty and volatility. For example, firms are on average larger in richer countries (see, e.g., Bento and Restuccia, 2017, and Poschke, 2014), and larger firms are also less volatile because they aggregate across more clients and lines of business (see, e.g., Davis et al., 2006). Could these differences in average firm size explain the decline of uncertainty and volatility with GDP per capita?

Columns (1) of Tables 3 and 4 dispel those concerns by controlling for first-order differences in our samples across countries, namely log(Employment) and sector fixed effects that capture differences in industrial composition across countries. We also include quarter fixed effects and an index of mobility around transit stations at the time of each country's survey wave, to control for high-frequency business cycle effects of the pandemic. We estimate large and significant coefficients on GDP per capita, equal to -0.05 for uncertainty in Table 3 and -0.11 for absolute forecast errors in Table 4. Average uncertainty rises by about 0.09 (half of the sample average of 0.18) when moving from a country with \$30,000 GDP per capita to another with just \$5,000 ($0.09 = -0.05 \cdot (\log(5000) - \log(30000))$). The drop in absolute forecast errors is 0.20, also about half its sample average from Table 2.

Can within-country predictors of uncertainty or volatility knock out GDP per capita from the regression? The second column of Tables 3 and 4 suggests otherwise. Motivated by Figure 2c we add the absolute value of recent changes in sales as a cross-sectional predictor of uncertainty in Table 3. Similarly, we add uncertainty at the time of forecast as a predictor of future absolute forecast errors in Table 4, as suggested by Figure 2b. Capturing cross-firm heterogeneity in this way results in a modest reduction of the GDP per capita coefficient. The estimates look similar as we add more macro controls in the remaining columns, including the coefficient of variation of GDP in the decade prior to the pandemic; exchange rate volatility in the 30 days prior to the survey; and dispersion in expected sales changes within a country-wave-sector. The coefficient drops by more in column (6) when we add exchange-rate regime dummies. That likely reflects systematic differences in the way rich and poor countries manage their exchange rates and handle monetary policy, and is not necessarily inconsistent with our broad finding.[11]

[11]We obtain data on exchange rate regimes from the 2019 Annual Report on Exchange Arrangements and Exchange Restrictions. Recent reports can be obtained at: https://www.elibrary-areaer.imf.org/Pages/YearlyReports.aspx .

Table 3: **Uncertainty Declines with GDP per Capita**

	(1)	(2)	(3)	(4)	(5)	(6)
	Subjective Uncertainty					
GDP per capita (log)	-0.050^{***}	-0.040^{***}	-0.038^{***}	-0.036^{***}	-0.034^{***}	-0.027^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Absolute change in sales		0.108^{***}	0.108^{***}	0.103^{***}	0.100^{***}	0.100^{***}
		(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
GDP SD 09-19 / Mean			0.462^{**}	0.445^{**}	0.482^{**}	0.742^{***}
			(0.223)	(0.217)	(0.233)	(0.210)
SD (arc) change in sales same country-wave-sector				0.077^{***}	0.081^{***}	0.074^{**}
				(0.029)	(0.031)	(0.031)
Exchange rate volatility last 30 days					0.278	0.863^{***}
					(0.200)	(0.284)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,734	25,892	25,892	25,892	24,859	24,859
Within R^2	0.079	0.157	0.161	0.164	0.164	0.174
No. of clusters	195	195	195	195	185	185

Notes: The table reports linear regressions with subjective business uncertainty about six-months-ahead sales (relative to the same period in the prior year) as the dependent variable. We measure GDP per capita in 2019 US dollars at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in from 2009 to 2019. SD (arc) change in sales is the standard deviation of arc-changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. The *Mobility* variable is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. The size control is log(Employment). We report heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **GDP per Capita and Subjective Uncertainty Independently Predict Absolute Forecast Errors**

	(1)	(2)	(3)	(4)	(5)	(6)
	Absolute Forecast Error					
GDP per capita (log)	-0.110^{***}	-0.094^{***}	-0.094^{***}	-0.079^{**}	-0.079^{***}	-0.034
	(0.029)	(0.029)	(0.031)	(0.031)	(0.029)	(0.023)
Uncertainty in previous wave (md)		0.275^{***}	0.275^{***}	0.260^{***}	0.252^{***}	0.226^{***}
		(0.085)	(0.085)	(0.087)	(0.086)	(0.083)
GDP SD 09-19 / Mean			-0.018	-0.373	-1.079	-1.809
			(1.307)	(1.333)	(1.461)	(1.687)
SD (arc) change in sales same country-wave-sector				0.327^{**}	0.342^{***}	0.369^{***}
				(0.139)	(0.130)	(0.116)
Exchange rate volatility last 30 days					-2.066^{*}	-1.035^{*}
					(1.106)	(0.606)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,659	4,659	4,659	4,657	4,657	4,657
Within R^2	0.055	0.072	0.072	0.083	0.089	0.101
No. of clusters	88	88	88	86	86	86

Notes: The table shows firm-level linear regressions with firm volatility measured by absolute forecast errors about six-months-ahead sales (relative to the same period in the prior year). During a first interview, managers provide a subjective probability distribution for future sales which we use to measure expectations (i.e. forecasts) and subjective uncertainty. During a follow-up interview, they report sales levels in the past 30 days, relative to the prior year, and we measure forecast errors as the difference between these realized sales and the forecast from the first interview. We measure GDP per capita in 2019 US dollars and purchasing power parity. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in. The *Mobility* variable is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. The size control is log(Employment). See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. We report heteroskedasticity-robust standard errors, clustered at the country-sector level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Tables A.4 to A.9 repeat the regression analysis from Tables 3 and 4 on subsamples of our World Bank data to further argue that our results are not driven by differences in the nature or quality of the sample across countries. Tables A.4 and A.7 run the analysis on the manufacturing sector only. Tables A.5 and A.8 focus on medium-sized firms with 20 to 99 employees. Finally, Tables A.6 and A.9 drop observations where we need to impute the probability vector before measuring expectations and uncertainty. In every subsample, we obtain large and significant coefficients in columns (1) and (2), so our baseline results hold even when we standardize the sample across countries and discard responses from managers who do not provide a distribution with three support points and probabilities that add to 100. After adding macro controls, the coefficient on GDP declines modestly but remains statistically significant in all but one of those tables.

By contrast, we find little evidence of systematic variation in business expectations with economic development. Table A.3 in the appendix follows the same format as Tables 3 and 4 but shows no conclusive relationship between GDP per capita and expected sales changes. Neither do Figures A.4e and A.4f which, respectively, plot the raw relationship by country-wave and in a firm level binscatter using the methodology of Cattaneo et al. (2024) to control for firm size, sector, and calendar quarter.

Our fact that subjective uncertainty about own-firm sales and realized sales volatility decline with GDP per capita echoes prior work by Koren and Tenreyro (2007) on macro volatility in poor versus rich countries. It is consistent with prior evidence that firm output, employment, and productivity are more volatile in poor countries, as documented by Haltiwanger et al. (2008), Asker et al. (2014), Donovan et al. (2018), and Moscoso Boedo (2018). It also relates to work that shows rich-country managers invest in forecasting technologies that may be out of reach in poor ones (e.g. Asriyan and Kohlhas, 2025; Charoenwong et al., 2024) Our contribution relative to that work is in showing that poor-country managers express systematically higher uncertainty and are subject to more volatility even *conditional on managers' information sets*. Thus, volatility and dispersion in poor countries are not due to higher measurement error, (see, e.g., Bils et al., 2021) or forecastable variation that managers can plan for. They reflect higher cash flow risks among poor-country firms, which their managers recognize when projecting future sales outcomes. Our results are also consistent with the higher cross-sectional dispersion of firm-level productivity in less-developed economies documented by Ayerst et al. (2024).

We do not establish a causal link between uncertainty or volatility and GDP per capita. One hypothesis for why managers are more uncertain and firms are more volatile in poor countries is that weak institutions keep countries poor and also make businesses riskier. Table A.2 in the appendix tests whether cross-country differences in perceived corruption

and trust of others explain away the patterns between GDP per capita and uncertainty. They do not, at least for the subset of countries where we have the necessary data. The coefficients on those indicators are small and statistically insignificant in columns (1) and (2). We also explore whether the gender of the manager or an indicator that the firm is an exporter matters for our results in columns (3) and (4). If the prevalence of women-led businesses and access to international markets indicate strong institutions, we would expect them to weaken GDP per capita's ability to predict sales uncertainty. Instead, we find higher coefficients in columns (3) and (4) than in (1) and (2). Given long-standing debates about how to causally link institutions and economic development (see, e.g., Glaeser et al., 2004; Acemoglu et al., 2005), we limit our contribution to documenting the robust relationship between uncertainty, volatility, and GDP per capita. Below we develop a quantitative model to match those empirical patterns and study their implications, while remaining agnostic about the underlying source of our facts.

3.2 Managers are *overprecise*, and especially so in low-volatility rich countries

Our second new fact is that managerial subjective uncertainty systematically understates realized volatility in all countries where we can track firm outcomes. Namely, managers are *overprecise* as in Ben-David et al. (2013), Boutros et al. (2020), and Barrero (2022). Our cross-country data on manager perceptions of uncertainty gives us a unique position to quantify managerial overprecision and compare its magnitude across countries.

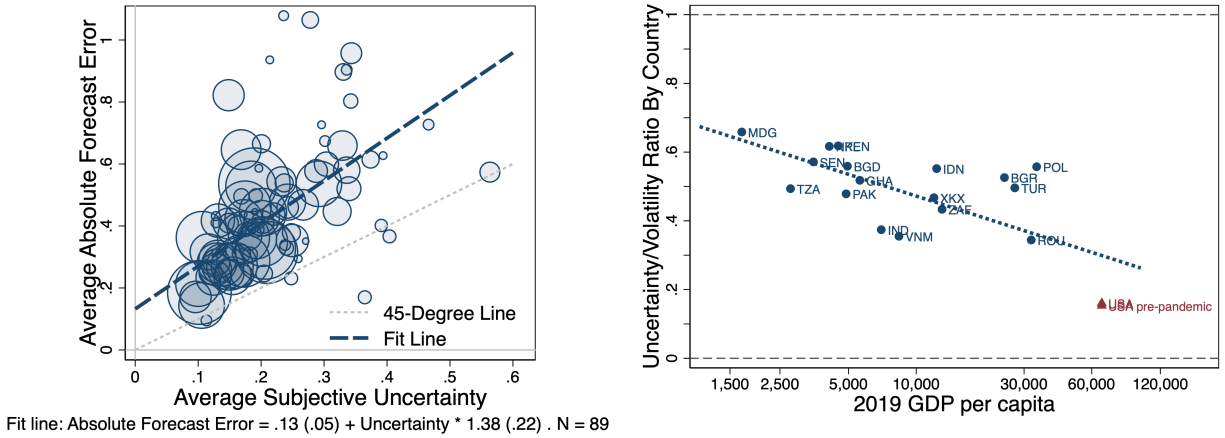
Figure 1b shows that sales volatility (i.e., average absolute forecast errors) exceeds uncertainty with 95% confidence in every country where we can measure both. The pattern extends to US data from the Atlanta Fed's Survey of Business Uncertainty. Our measures of uncertainty and volatility are deliberately analogous (see equations 2 and 3), except uncertainty comes from managers' (ex-ante) subjective distribution and volatility reflects (ex-post) sales outcomes. If managers had rational expectations and there were no large common shocks, we would expect average uncertainty to be about as large as average absolute forecast errors, and the data in Figure 1b would trace the 45-degree line. It does not, instead suggesting that managers systematically underestimate own-firm sales risk.

We find the same pattern when we compare average uncertainty and volatility across 89 country-sector combinations in the World Bank data, shown in Figure 3a. Each marker represents a country-sector and its size is proportional to the underlying number of forecast-error observations. Weighting by those sample sizes to avoid drawing inferences from country-sectors with few observations, Figure 3a reveals a positive relationship between uncertainty and volatility. The fit line is uniformly above the 45-degree line, as indicated by the intercept and slope estimates reported below the figure. Indeed, average

absolute forecast errors exceed subjective uncertainty in 85 of 89 country-sectors. Where it does not, we have very few observations and expect noisier averages.

Figure 3: **Managers are Overprecise in Most Country-Sectors, and Especially in Rich Countries**

(a) **Volatility vs. Uncertainty by Country-Sector** (b) **Rich-Country Managers are More Overprecise**



Notes: The chart on the left plots average absolute forecast errors against average subjective uncertainty, both computed at the country-sector level. The size of each each bubble is proportional to the number of forecast error observations in each country-sector. The chart on the right plots the ratio between average subjective uncertainty and average absolute forecast errors (volatility) against GDP per capita. Managers provide subjective probability distributions about six-months-ahead sales, relative to 2019, and we compute expectations (i.e. forecasts) and uncertainty based on those responses. We define absolute forecast errors as the absolute difference between realized sales in the 30 days prior to the follow-up interview and forecast sales from the initial interview. GDP per capita data are from 2019 and measured in 2019 US dollars at purchasing power parity rates.

In Figures 1a, 1b, and 3a the gap between average uncertainty and average absolute forecast errors is roughly constant as we move along the horizontal axis. The regression lines in Figures 1b and 3a also both estimate a constant of 0.1 and slope coefficients near 1. These empirical regularities suggest that managers underestimate volatility by a roughly constant (additive) amount across levels of uncertainty and GDP per capita. The corollary is that managers in low-volatility rich countries underestimate volatility by a higher *percentage*, a new contribution to the literature on managerial biases across countries.

Figure 3b corroborates that conclusion by plotting the ratio between average uncertainty and average volatility (absolute forecast errors) by country against GDP per capita, revealing a downward sloping relationship. All data points are far below 1, where we would expect them to be under rational expectations and without large common shocks to sales. Among poor countries with 2019 PPP GDP per capita under $2,500, ratios of about 0.6 imply that managers underestimate volatility by about 40%. In high-income countries, with GDP per capita over $30,000, ratios of 0.4 or less that imply underestimates of 60% or more. Thus, rich-country managers are much less attuned to sales volatility than their

counterparts in poor countries. Rich-country firms might be exposed to smaller shocks, but their managers perceive disproportionately less uncertainty.

What could be behind such strong overprecision among rich-country managers? A priori, we conjectured that better-educated or sophisticated managers, like those in rich countries, would be less overprecise. Perhaps the answer relates to corporate governance and CEO selection (see, e.g. Eisfeldt and Kuhnen, 2013). Salgado (2020) and Kozeniauskas (2023) link a decline in US entrepreneurship to better outside options (often with greater insurance) for skilled workers. If those outside options become more common at higher levels GDP per capita, that could skew the pool of potential business leaders in rich countries towards those who have good ideas and underestimate risk. Alternatively, rich-country firms might choose leaders who are resolute and take action swiftly, implicitly selecting overprecise managers who tune out risks (see, e.g., Bolton et al., 2013).

3.3 Do common shocks to output drive our measures of overprecision?

Some of the shocks that raise average volatility (absolute forecast errors) might be common across firms. A large and unforeseen decline in economic activity could inflate the average absolute forecast error without also raising subjective uncertainty. In our setting where we often have one or two forecast-error cross-sections by country, those concerns are especially important. We would not want to claim that managers suffer from an overprecision bias if our measures of volatility are dominated by one-off common shocks to sales.

We address these concerns by quantifying the contribution of common (country-wide) shocks in each country. We decompose the mean squared forecast error of each country into two components:

$$\text{Mean Squared Forecast Error} = \text{Bias}^2 + Var(\text{Forecast Error})$$

following standard statistical theory (see, e.g., the section on mean squared errors in Casella and Berger, 2024).[12] The two terms on the right-hand-side are the square of the average forecast error (i.e., the bias) and the variance of forecast errors in the country.

Figure 4a plots the total mean squared error (MSE) and the bias squared component in our main cross-country sample. It reveals a modest contribution of the bias squared term throughout, implying that common shocks are not the primary driver of measured volatility. Figure 4b corroborates this observation by plotting the ratio between bias

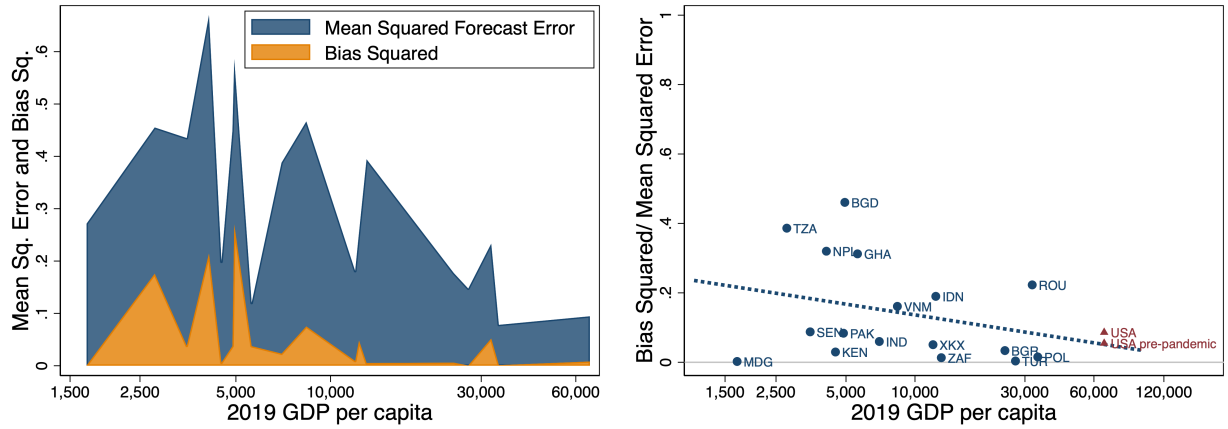
[12] In countries with multiple forecast-error cross-sections, we run the decomposition for each cross section and then recover the average contribution of bias from a weighted average of cross-sections: $\text{Mean Squared Forecast Error} = \sum_i \frac{n_i}{N} \text{Bias}_i^2 + \sum_i \frac{n_i}{N} Var_i(\text{Forecast Error})$. This procedure is especially important for our US data, where we have dozens of cross sections whose individual biases average out.

squared and mean squared error in each country against GDP per capita. All ratios are under 0.5, and under 0.3 in all but a handful of countries. The plot does reveal a negative relationship between the ratio and GDP per capita. That means one-off common shocks to sales seem to be a larger contributor to forecast errors in poor countries, consistent with Koren and Tenreyro (2007). The regression line, however, suggests that common shocks account for less than 20% of mean squared forecast errors in countries with less than $5,000 in GDP per capita, and about 5% in the US.

Figure 4: **Common Country-Level Shocks Contribute Modestly to Mean Squared Forecast Errors**

(a) **Bias Squared and Mean Squared Forecast Error Levels vs. GDP per Capita**

(b) **Bias Squared to Mean Squared Forecast Error Ratio vs. GDP per Capita**



Notes: The left chart plots the mean squared forecast error and bias squared by country against 2019 GDP per capita. The right chart plots the ratio between the two components against GDP per capita. Managers provide subjective probability distributions about six-months-ahead sales, relative to 2019, and we compute expectations (i.e. forecasts) and uncertainty based on those responses. We compute absolute forecast errors as the absolute difference between realized sales in the 30 days prior to the follow-up interview and forecast sales from the initial interview. GDP per capita data are from 2019 and measured in 2019 US dollars at purchasing power parity rates. We obtain the bias squared by averaging across (non-absolute) forecast errors and then squaring the result.

Our estimates of overprecision are also robust to dropping countries or country-sectors with large bias components, as Table A.10 shows in the appendix. We estimate an average difference between absolute forecast errors and uncertainty of about 0.2 and an average ratio of about 0.5, both of which barely change when we drop countries or country-sectors with larger bias components.[13]

Our evidence that managers are overprecise and that this is not driven by one-off macro shocks is consistent with prior work. Barrero (2022) examines US data underlying

[13]Figure A.7 in the appendix provides further evidence that our measures of overprecision do not hinge on countries or country-sectors in which forecast errors have larger biases. We plot these measures against the absolute bias and estimate a gap between uncertainty and absolute forecast errors even among countries with near-zero bias. In the country-sector samples, the estimated intercepts are highly significant and consistent with our headline measures of overprecision.

the pre-pandemic US point in Figure 1 and shows that managers underestimate sales risk. Ben-David et al. (2013) and Boutros et al. (2020) also report managerial overprecision with respect to S&P 500 returns going back to 2001, spanning multiple recessions and expansions. Our key contributions relative to this prior work are: (1) showing that managers also underestimate sales risk in 17 developing/emerging economies; (2) quantifying the contribution of common (macro) shocks; and (3) arguing that rich-country managers underestimate volatility by a larger *percentage*. The latter fact is particularly novel and raises questions about how managers make investment decisions differently in rich versus poor countries. Below, we build and quantify a dynamic model to study the implications of differential uncertainty, volatility, and overprecision on investment decisions and macro outcomes across countries.

4. A dynamic model featuring uncertainty, volatility, and real options

In the previous section we documented large differences in uncertainty, volatility, and overprecision across countries. To study the implications of those facts for firm-level and aggregate outcomes, we build a dynamic model in which managerial decisions depend on ex-ante uncertainty as well as realized volatility. If uncertainty is systematically smaller than ex-post volatility, managers are overprecise. We deliberately use a stylized model with limited frictions that can speak to our empirical facts, but in the appendix and robustness sections (see Section 5.4) we consider a number of extensions and alternative specifications that enrich this framework.

We model an economy that takes the world interest rate r as given and focus on stationary equilibriums with labor market clearing. Without loss of generality, we normalize aggregate labor supply to one. To keep the notation light, we use lowercase letters to refer to firm-specific variables and uppercase letters to refer to aggregates and value functions. We denote one-period-ahead variables using primes ($'$).

4.1 Production and variable profits

A unit mass of entrepreneurs manage their own business by investing in capital k and hiring labor n locally. Businesses produce revenue $\hat{y}$ using a decreasing-returns production technology subject to an idiosyncratic shock $\hat{z}$ and a country-wide total-factor-productivity shifter $\hat{A}$:

$$\hat{y} = \hat{A}\hat{z}\left(k^{\hat{\alpha}}n^{1-\hat{\alpha}}\right)^{\nu}, \tag{4}$$

where $\nu \in (0,1)$ governs decreasing returns to scale and $\hat{\alpha}$ governs the capital share.

Each period, managers hire labor to maximize profits, taking the equilibrium wage w

and their current capital stock k as given. After optimizing, variable profits are proportional to output, and we can write them down as a function of capital and two TFP shifters for idiosyncratic (z) and aggregate (A), that are simple transformations of their counterparts in equation 4:[14]

$$\underbrace{Azk^{\alpha}}_{\text{variable profit}} \equiv \max_{n} \hat{A}\hat{z}\left(k^{\hat{\alpha}}n^{1-\hat{\alpha}}\right)^{\nu} - wn,$$

where $\alpha \equiv \frac{\hat{\alpha}\nu}{1-(1-\hat{\alpha})\nu} < 1$. Due to the Cobb-Douglas functional form, the growth rates of output and variable profit growth are equal.[15]

4.2 Shocks to firm profitability and managerial forecasting

Firm cash flows are subject to idiosyncratic profitability risk that follows an AR(1) process:

$$\log(z') = \rho \log(z) + \sigma\varepsilon' \tag{5}$$

where $\varepsilon \sim \mathcal{N}(0,1)$ and is independent across firms and time. Managers forecast future z' using a subjective stochastic process whose conditional volatility $\tilde{\sigma}$ can differ from the true volatility σ:

$$\log(z') = \rho \log(z) + \tilde{\sigma}\varepsilon'. \tag{6}$$

They are overprecise (underestimate the conditional volatility) if and only if $\tilde{\sigma} < \sigma$. This specification for the beliefs process is a reduced form, but can be derived from a setup where managers receive a signal of future profitability and they overestimate the precision of that signal. Alti and Tetlock (2014), for example, model managerial overprecision in this way to explain asset pricing anomalies. Boutros et al. (2020) also microfound overprecision within a Bayesian learning framework, and Bianchi et al. (2024) derive it by generalizing the diagnostic expectations model of Gennaioli and Shleifer (2010) and Bordalo et al. (2018).

4.3 Managerial investment decisions

Managers observe their firm's current profitability z and capital k and choose how much to invest to obtain capital k' next period. The law of motion for capital takes into account depreciation and investment, so that $k' = i + k(1-\delta)$.

Investment is subject to adjustment costs. We focus on partial irreversibility, whereby buying a unit of capital lowers the firm's free cash flows by one unit, but the resale price for that unit of capital yields a loss of $\gamma \in [0,1]$. This resale loss captures any firm-specificity

[14] Specifically, $A \equiv \hat{A}^{\frac{1}{1-(1-\hat{\alpha})\nu}} w^{\frac{-(1-\hat{\alpha})\nu}{1-(1-\hat{\alpha})\nu)}} \left([(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu\right)$ and $z \equiv \hat{z}^{\frac{1}{1-(1-\hat{\alpha})\nu}}$.

[15] Additionally, the firm's labor choice $n^*(z,k;w) \equiv \arg\max_n \hat{A}\hat{z}(k^{\hat{\alpha}}n^{1-\hat{\alpha}}) - wn$ is proportional to output.

of investment, for example. The model can support other forms of adjustment costs, but we focus on partial irreversibility because γ has a clear economic interpretation and we don't have direct data on investment. That said, we are interested in how uncertainty and volatility affect managerial investment decisions. Partial irreversibility is a minimal modeling device (with empirical support in Cooper and Haltiwanger (2006) and Bloom, 2009) by which subjective uncertainty $\tilde{\sigma}$ can shift managers' subjective valuation of real investment options and thereby their decisions. If we instead had detailed panel data on investment, we might have modeled and estimated a flexible adjustment cost function.

The firm's free cash flows are equal to profits adjusted for investment activities:

$$\pi(z,k,k') \equiv Azk^{\alpha} - [k' - (1-\delta)k] \cdot [1 - \gamma \cdot \mathbf{1}(k' < (1-\delta)k)] \,.$$

If the manager's choices result in negative free cash flows, they bring in outside capital. Positive free cash flows get distributed to the manager-entrepreneur who owns the business.

We assume managers maximize the net present value of cash flows, discounted at the world interest rate r that they take as given. Incumbent managers' dynamic programming problem is therefore:

$$\tilde{V}(z,k) \;\; = \;\; \max_{k'} \left\{ \pi(z,k,k') + \frac{1}{1+r} \widetilde{\mathbf{E}}[\tilde{V}(z',k')] \right\}$$

In words, managers choose capital next period k' to maximize the sum of current cash flows and the discounted expected continuation value of the firm $\widetilde{\mathbf{E}}[\tilde{V}(z',k')]$. Their subjective valuation of the business $\tilde{V}(z,k)$ solves the functional equation above, in which the operator $\widetilde{\mathbf{E}}[\cdot]$ takes expectations under the manager's subjective stochastic process for future profitability z' from equation 6. Making profitability and, implicitly, sales projections central to investment decisions is consistent with actual capital budgeting practices reviewed by Graham (2022).

4.4 Stationary equilibrium

A stationary equilibrium is characterized by manager valuations of their businesses $\tilde{V}(z,k)$, a wage w, and a stationary distribution of firms $\phi(z,k)$ such that:

- $\tilde{V}(z,k)$ solves the manager's problem;
- The stationary distribution of firms across the state space $\phi(z,k)$ is consistent with

manager investment policies $k^*(\cdot)$ and the law of motion of profitability $Pr(z'|z)$:

$$\phi(z', k') = \int_{z,k} Pr(z'|z) \cdot \mathbf{1}(k^*(z,k) = k') \cdot \phi(z,k) \mathrm{d}z \mathrm{d}k;$$

- The labor market clears, so $\int_{z,k} n^*(z,k;w)\phi(z,k)\mathrm{d}z\mathrm{d}k = 1$ and labor $n^*(\cdot)$ follows from static profit maximization.

Aggregate value added (the analog to GDP in the data) in equilibrium is the sum of output across all firms in the economy. After choosing its optimal labor, a firm's output is proportional to variable profits:

$$\hat{A}\hat{z}k^{\tilde{\alpha}\nu}(n^*)^{(1-\tilde{\alpha})\nu} = Azk^{\alpha}\frac{[(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu}}{(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu}.$$

Therefore, aggregate value added is:

$$Y = \int_{z,k} \left[\frac{[(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu}}{(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu} Azk^{\alpha}\right] \cdot \phi(z,k)\mathrm{d}z\mathrm{d}k.$$

We solve the model numerically on a discretized state space, using value-function iteration to obtain $\tilde{V}(\cdot)$ and $k^*(\cdot)$. Then we use a non-stochastic simulation method that combines the stochastic process for z and investment rules $k^*(\cdot)$ to numerically approximate the stationary distribution $\phi(z,k)$.

4.5 Mapping expectations, uncertainty, and volatility between the model and the data

The key moments from our empirical results all have natural analogs in the model. Let y^- be sales in the prior year, which is the benchmark for future sales in our survey data, and hold fixed the manager's information set in the current period. Then,

- the manager's expected change in sales is $\widetilde{\mathbf{E}}[g'] \equiv \widetilde{\mathbf{E}}\left[\frac{y'-y^-}{\frac{1}{2}(y'+y^-)}\right]$;
- the firm's actual change in sales is $g' \equiv \frac{y'-y^-}{\frac{1}{2}(y'+y^-)}$;
- the manager's subjective uncertainty is given by $\widetilde{\mathbf{E}}\left[|g' - \widetilde{\mathbf{E}}[g']|\right]$;
- the manager's absolute forecast error is $|g' - \widetilde{\mathbf{E}}[g']|$.

We can compute employment-weighted averages of these objects from the stationary distribution of the model and match them to analogous measures in the survey data. To obtain the subjective moments, we combine knowledge of managers' investment rules

$k^*(z,k)$ and the subjective process they use to forecast future profitability z' from equation 6. For realized volatility, we combine the objective process for profitability from equation 5 with managerial forecasts and their investment rules. Because we work with one-period-ahead forecasts, subjective uncertainty and realized volatility are largely determined by $\tilde{\sigma}$ and σ, the parameters that govern the conditional volatility of shocks to $\log(z')$ in the subjective and objective processes, respectively.

4.6 Small sample bias in sales forecasts

We assume there is an i.i.d., economy-wide shock to realized output after equilibrium conditions are set in our model. Firm-level output next period is therefore $y' = z'k'^{\alpha} \cdot (1+\mathcal{A}')$, where the unforecastable common shock $\mathcal{A}'$ generates a small-sample bias in managerial forecasts. In the absence of this shock, forecasts are unbiased in the model because the subjective and objective stochastic processes for $\log(z')$ have the same conditional and unconditional mean (see equations 5 and 6). By calibrating this common shock, we let our model match a key feature of our data shown in Figure 4. Namely, country-wide shocks contribute modestly but non-trivially to mean squared forecast errors at the country level – especially in poor countries. Average absolute forecast errors therefore depends on the common shock $\mathcal{A}'$ and the objective volatility σ of z'.

5. Implications of cross-country differences in uncertainty and volatility

We run a series of calibration exercises to study how manager perceptions of uncertainty versus realized volatility impact investment, capital reallocation, and output across countries. In particular, we want to know whether high volatility and modest overprecision explains poor countries' low capital accumulation and GDP per capita.

5.1 Setup and target moments

Our calibrations consider four hypothetical economies defined by their relative GDP per capita. The first is a high-income country with PPP GDP per capita of \$66,000 in 2019, comparable to the US. The second's GDP per capita is half as large, comparable to Poland and near the top of our World Bank sample. The third has GDP per capita of \$15,000, 23% as high as the US and comparable to Brazil. The fourth's is \$5,000, about 8% as high as the US and similar to Kenya. For each economy, we find a vector of parameters that matches our facts about uncertainty and volatility conditional on relative GDP per capita. We set the model period to be a half-year, consistent with the look-ahead horizon of the expectations and uncertainty data from Sections 2 and 3.

Table 5: **Calibration Targets and Relevant Parameters**

Comparable Country	Relative GDP/person	Uncertainty	Abs. Forecast Errors	Bias^2/ MSE	Capital-Output (K/Y) Ratio
US	1.00	0.05	0.22	0.05	4.31
Poland	0.50	0.09	0.28	0.08	
Brazil	0.23	0.14	0.35	0.12	
Kenya	0.08	0.20	0.44	0.17	
Key Parameter	A TFP	$\tilde{\sigma}$ Subj. SD	σ Obj. SD	$\mathcal{A}'$ Comm. Shock	$\hat{\alpha}$ Capital Share

Notes: This table shows the moments that we target in our calibration. Each model period is one half-year. We use the cross-country line of best fit for uncertainty, forecast errors, and the Bias^2/MSE ratio against log(GDP per capita) to obtain the target values for 4 simulated countries with PPP GDP/person of \$66,000, \$33,000, \$15,000 and \$5,000. We use a regression of capital-output ratios against log(GDP per capita) to obtain that target for the high-income economy. Note that GDP and GDP per Capita are equal in our model economies because we normalize aggregate labor supply across countries. See Section 4.

Table 5 shows the key target moments for each economy. They are employment-weighted average subjective uncertainty and absolute forecast errors, and the ratio of squared forecast bias to mean squared forecast error. We compute each of those moments as a functions of log(GDP per capita), based on the linear regressions in our empirical work. Specifically, we take the regression lines from Figures 1a and 4b and evaluate them at log(66,000), log(33,000), log(15,000) and log(5,000), obtaining the values for each hypothetical economy. We do not target data points from individual countries in the data to focus on the systematic variation between uncertainty, volatility, and GDP per capita, drowning out the noise in the data.

To anchor aggregate investment outcomes in our model at an empirically plausible level, we also target the capital-output (K/Y) ratio of the high-income economy. We obtain data on 2017 PPP capital stocks and GDP for the US and other countries in our World Bank sample from the Penn World Table (Feenstra et al., 2015). Then we regress their capital-output ratios against log(GDP per capita) and evaluate the regression line at log(66,000) to obtain a target of 4.31 for the high-income economy. The underlying regression yields a positive slope of 0.63 and a standard error of 0.15. Broader samples with 150+ countries yield modestly flatter slopes between 0.5 and 0.6.

Our calibration exercises seek a vector of parameters, shown in the bottom row of Table 5, that match the target moments for each hypothetical economy. For the full calibration of the high-income economy, that includes the capital share of physical output $\hat{\alpha}$, which we then use for the other economies. Given a vector $\{A, \sigma, \tilde{\sigma}, \mathcal{A}'\}$ (plus $\hat{\alpha}$ for the high-income economy), we obtain model-implied versions of the target moments and search for the combination of those parameters that minimizes the sum of squared deviations between

model-implied and data moments.[16] We run this minimization using an identity weight matrix because the problem is exactly identified and we can match the data moments very closely (up to the third decimal point in most cases).[17]

Table 5 associates each key parameter to a target moment based on an intuitive mapping between them. Holding other parameters fixed:

- the country-wide TFP shifter A governs relative GDP per capita because it scales the overall productivity of firms in each country;
- the conditional volatility of the subjective distribution $\tilde{\sigma}$ governs the average level of sales uncertainty that managers perceive;
- the conditional volatility of the objective shock process σ governs the magnitude of unforecastable sales shocks and therefore of average absolute forecast errors;
- the common shock to output $\mathcal{A}'$ introduces an average bias, raising the ratio of bias squared to mean squared forecast error;
- the capital share $\hat{\alpha}$ raises investment returns to scale and thereby raises the aggregate capital-output (K/Y) ratio.

Of course, all parameters can change the value of all moments, but we conduct comparative static exercises that confirm our intuitive mapping.

Each simulation holds fixed another set of parameters, shown in Table 6, based on standard calibrations for the US. They govern the technology, shock persistence, and investment frictions, which we hold constant across economies and calibrations. We calibrate the capital share of physical output to yield a capital-output ratio of 4.3 for the high-income economy, and hold it fixed elsewhere. We assume revenue returns-to-scale of 0.80 in physical output (consistent with with 25% markups), implying a returns-to-scale elasticity α of 0.66 for the variable profit function. The autocorrelation of profitability shocks $\log(z)$ is based the 0.95 quarterly rate in Khan and Thomas (2008). The degree of investment irreversibility, with resale losses of 30%, is slightly lower than corresponding estimates in Bloom (2009) and in the ballpark of typical estimates.

[16] We compute our simulated moments as similarly to the empirical moments as possible. For example, the survey asks managers to report future outcomes for the firm's sales relative to the prior year. Our empirical measures of expectations and uncertainty express those future outcomes as arc-changes relative to the same period in the prior year, and then compute the expectation and standard deviation using the probabilities provided by the manager. We mimic that procedure in the model. Similarly, country-level measures of uncertainty and volatility are employment-weighted averages in both the data and the model.

[17] For the full model and the high-income country, we put a weight of $1/10$ on the target capital output ratio because it is one order of magnitude larger than the other moments. Without this adjustment, the minimization would implicitly put disproportionate weight on matching the capital-output ratio.

Table 6: **Calibration: Fixed Parameters**

Parameter	Description	Value	Notes/Target
$\hat{\alpha}$	Capital share, output	0.48	$\frac{K}{Y} = 4.3$ at relative GDP/person of 1.0
ν	Decreasing returns, output	0.80	25% markups
α	Decreasing returns, var. profit	0.66	$\hat{\alpha}\nu/(1-(1-\hat{\alpha})\nu)$
ρ	$Corr(\log(z'), \log(z))$	0.90	.95/qtr., cf. Khan and Thomas (2008)
δ	Depreciation	0.05	10% annual
γ	Capital resale loss	0.30	30% resale loss
r	Discount rate	0.01	2% annual

Notes: This table shows the parameters for the technology, investment frictions, and discount rate that we hold constant across the calibrations of the model that fit GDP-per-capita gaps, uncertainty, absolute forecast errors across countries. One model period is equivalent to a half-year.

By fixing the parameters in Table 6 across countries, we force $\{A, \sigma, \tilde{\sigma}, \mathcal{A}'\}$ do all the work of explaining cross-country differences in uncertainty, volatility, and GDP per capita. Thus, our calibrations are effectively development accounting exercises that match GDP per capita gaps, and the resulting country TFP shifters are residual, reduced form parameters that match those gaps conditional on other parameters and moments.

5.2 High volatility and low overprecision imply low capital-output ratios and wide TFP gaps in poor countries

We run three sets of counterfactual calibrations to understand how our facts about uncertainty and volatility matter for cross-country investment, productivity, and reallocation. The first is a "full" calibration that fits our facts from Section 3, targeting uncertainty, volatility, and common shocks conditional on GDP per capita as shown in Table 5. The second set abstracts from managerial overprecision (it imposes rational expectations) while acknowledging cross-country differences in volatility and common shocks. This second set of calibrations lets σ and $\mathcal{A}'$ differ by country based fo fit absolute forecast errors and bias squared to mean squared error ratios, but forces $\tilde{\sigma} = \sigma$ in every economy. The final set of calibrations matches our hypothetical economies' GDP per capita gaps while ignoring our facts. It assumes idiosyncratic volatility and common shocks are uniform across countries at the level of the high-income economy, while also abstracting from overprecision. That means $\tilde{\sigma} = \sigma = 0.28$ and $\mathcal{A}' = 0.07$ everywhere in this final set of calibrations.

Table 7 reports the parameters from the three sets of counterfactual calibrations, with Table 7a corresponding to the first (full) exercise, 7b to the second, and 7c corresponding to the third, which abstracts from our facts. Table 7a also reports the degree of overprecision implied by our facts, expressed as a ratio between the subjective and objective volatility

Table 7: **Calibrated Parameters**

(a) **Full Exercise: Country-Specific Volatility, Uncertainty, and Bias^2/MSE**

Parameter	Description	Relative GDP per Capita:			
		1.00	**0.50**	**0.23**	**0.08**
$\hat{A}$	Relative TFP	1.00	0.59	0.30	0.11
$\tilde{\sigma}$	Subjective volatility	0.05	0.10	0.17	0.28
σ	Objective volatility	0.28	0.36	0.47	0.63
$\mathcal{A}$	Common shock to sales	0.07	0.11	0.17	0.24
$\tilde{\sigma}/\sigma$	Overprecision ratio	0.19	0.29	0.37	0.44

(b) **Country-Specific Volatility and Bias^2/MSE, No Overprecision**

Parameter	Description	Relative GDP per Capita:			
		1.00	**0.50**	**0.23**	**0.08**
$\hat{A}$	Relative TFP	1.00	0.58	0.29	0.10
σ	Objective volatility	0.28	0.36	0.46	0.63
$\mathcal{A}$	Common shock to sales	0.07	0.11	0.17	0.25

(c) **Rich-Country Volatility and Bias^2/MSE, No Overprecision**

Parameter	Description	Relative GDP per Capita:			
		1.00	**0.50**	**0.23**	**0.08**
$\hat{A}$	Relative TFP	1.00	0.65	0.40	0.21
σ	Objective volatility	0.28	0.28	0.28	0.28
$\mathcal{A}$	Common shock to sales	0.07	0.07	0.07	0.07

Notes: This table shows the parameters that match the moments targeted in three sets of counterfactual calibrations of our model. Table 7a shows the results from the full exercise where we match relative the five targets from the data, namely: relative GDP per capita, volatility (average absolute forecast errors), uncertainty, bias squared to mean squared error ratios, and the exit rate. The version in Table 7b allows for differences in volatility and bias to mean-quared error ratios across countries but sets the subjective volatility $\tilde{\sigma}$ equal to the objective volatility σ. The version in Table 7c assumes volatility and bias' contribution to mean squared forecast errors across all countries are the same as for a country with US-level GDP per capita ($66,000 in 2019 at PPP).

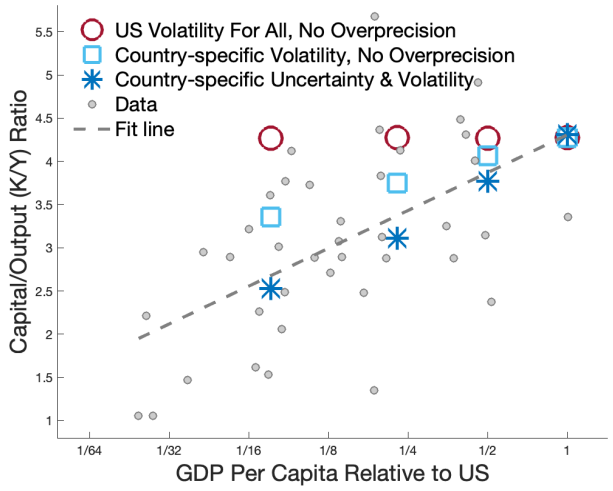
parameters ($\tilde{\sigma}/\sigma$) in each economy. We obtain lower ratios at higher levels of GDP per capita, confirming our reasoning from Section 3 that overprecision is more severe in richer countries. These measures of overprecision are far below one (where we would expect them to be under rational expectations) even though we allow for common shocks $\mathcal{A}'$

that amplify mean squared errors relative to subjective uncertainty (see Figure 4b). Thus, our quantitative exercises rule out large common shocks as the primary driver of our overprecision statistics.

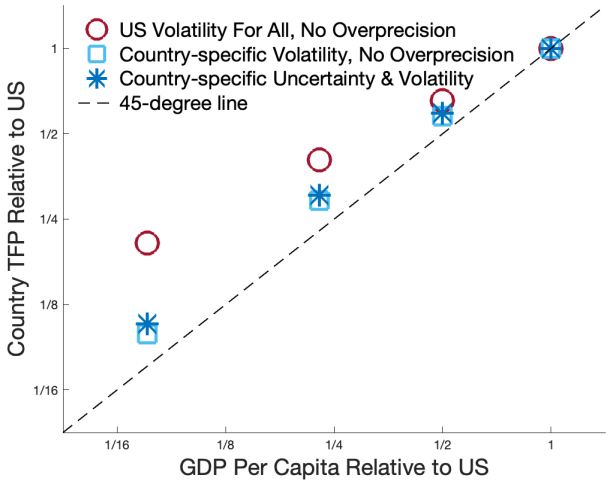
The calibration exercises reveal two key implications of our facts, shown in Figure 5. First, the blue asterisks in Figure 5a show our full calibration with high volatility and modest overprecision in poor countries matches the upward-sloping relationship between aggregate capital-output (K/Y) ratios and log(GDP per capita) in the data. The figure also shows the scatter plot of data points for our sample of countries and the resulting fit line, with a slope of 0.63 compared to 0.69 in the model. That empirical upward-sloping relationship is consistent with a long literature linking economic development to capital investment, including Caselli (2005) and Hsieh and Klenow (2010).

Figure 5: **Our Facts Imply Upward-Sloping Capital-Output Ratios and Large Cross-Country TFP Gaps**

(a) **Capital-Output (K/Y) Ratios vs. GDP per Capita**



(b) **Relative TFP vs. GDP Per Capita**



Notes: Figure 5a plots data on 2017 aggregate capital-output (K/Y) ratios (source: Penn World Table, Feenstra et al., 2015) for 39 countries from our sample against GDP per capita, along with the regression fit line. We drop Tajikistan because it has an implausibly high capital-output ratio of more than 9, and have no data for Kosovo or Afghanistan in 2017. It also superimposes the capital-output ratios implied by the three calibrations of our model. Figure 5b plots the relative TFP parameters across the three calibrations against relative GDP per capita. See Table 7 for more details. See Table 5 for more about the relative GDP per capita statistics that we target.

Figure 5a serves an overidentifying test of our model. We match the level of the fit line by construction, as our calibration of $\hat{\alpha}$ anchors the high income country's capital-output ratio to the fitted value of 4.3. But we do not target the slope or other economies' capital-output ratios. Critically, the relationship breaks down when we ignore some or all of the facts we document in Section 3. Assuming away overprecision in our second set of

calibrations, the model yields a slope of 0.36 – about half as large as in the data – traced by the light blue squares in the figure. When we additionally ignore cross-country differences in volatility in the third set of calibrations, we obtain a counterfactual, flat relationship between capital-output ratios and GDP per capita, traced by the red circles in Figure 5a.

These patterns imply that cash flow volatility and managerial perceptions of uncertainty are key cross-country determinants of capital budgeting and investment. All of our calibration exercises can fit cross-country GDP per capita gaps by choosing the right TFP residuals. But we can only explain why poor countries have low capital-output ratios when we fit the model to our facts about uncertainty and volatility. Moreover, a behavioral distortion – managerial overprecision – accounts for half of the gradient between capital-output ratios and economic development. Thus, we provide a new explanation for this long-standing phenomenon that the macro-development literature has grappled with for decades, making capital budgeting practices central to economic development.

Our success at matching capital-output ratios does not come for free, however. Figure 5b reveals a second key implication of our quantitative exercises: our facts imply larger TFP gaps across countries. The figure plots the country-wide TFP shifters that come out of each set of calibrations against relative GDP per capita.[18] Again, the red circles correspond to the calibration exercise that abstracts from our facts; the light blue squares come from the version that match cross-country differences in volatility and common shocks; and the blue asterisks correspond to the third (full) version that also match subjective uncertainty and overprecision by country.

We infer *lower* TFP in developing/emerging economies when we match their higher levels of realized sales volatility. That effect gets dampened when when we match the degree of managerial overprecision, but the TFP shifters are still lower in the full calibration than in the one that ignores our empirical evidence. Thus, our facts and model imply larger gaps in residual, cross-country TFP. At a relative GDP per capita of 0.5, the effect is modest. Matching our facts depresses the TFP residual by 10% compared with the calibration that imposes uniform-cross-country volatility and rational expectations. But that number jumps to 25% and 48% at relative GDP per capita of 0.23 and 0.08, respectively.

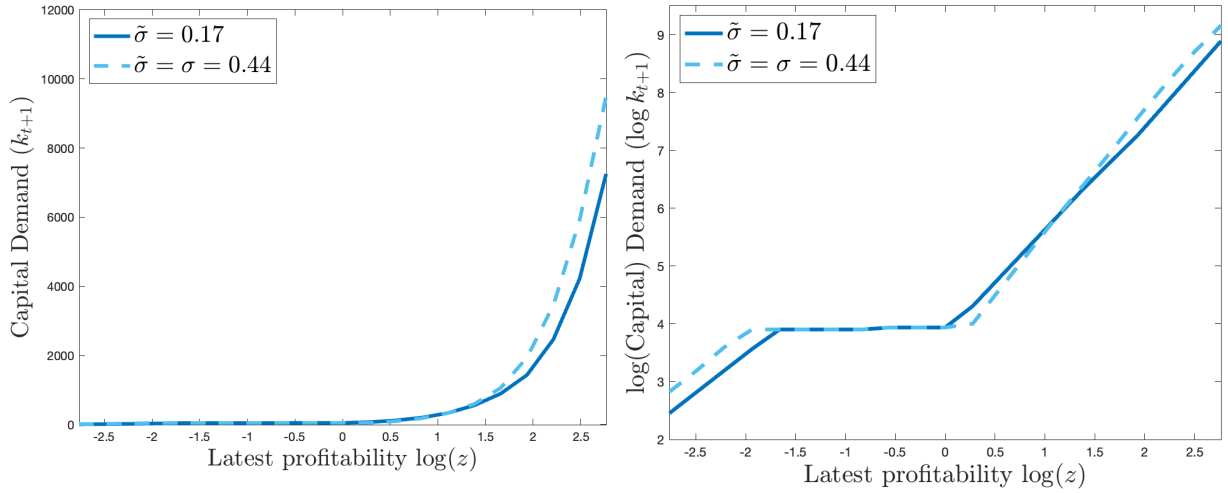
[18]Figure 5 and our results below focus on relative TFP shifters of the value-added production function $\hat{A}$ instead of the variable profit shifter A. The reason is that we care more about the ability to generate value added than variable profits. That said, there is a one-to-one mapping between $\hat{A}$ and A that depends only on fixed parameters and the equilibrium wage. See the discussion in Section 4.1.

5.3 Why do uncertainty and volatility matter for investment and productivity?

To understand why high uncertainty and volatility lead to low capital-output ratios and low TFP residuals in poor countries, it is useful to examine the policy function that describes managerial demand for capital. We plot it in levels (left) and logs (right) in Figure 6 for two different levels of subjective volatility $\tilde{\sigma}$ based on the parameterization for the country with relative GDP of 0.23.

Figure 6: **Demand for Capital is Convex in Profitability. Uncertainty Dampens Reallocation Away From Low-Productivity Firms**

(a) **Capital Demand in Levels** (b) **Capital Demand in Logs**



Notes: The figures show capital demand as a function of profitability $\log(z)$. Both figures use are for firms in the country with relative GDP per capita of 0.23, comparing the policy functions of managers who perceive uncertainty based on our calibrated value of $\tilde{\sigma}$ or under the objective value σ.

Managerial demand for capital is convex in log-profitability $\log(z)$, as the left panel of Figure 6 shows. That convexity generates an Oi-Hartman-Abel or volatility effect, whereby a rise in σ (the volatility of $\log(z)$) creates growth and investment opportunities for some lucky firms that get large profitability shocks (see Oi, 1961; Hartman, 1972; Abel, 1983). It also raises firm value, as Figure A.11 shows in the appendix. Convexity in the demand for capital arises naturally from decreasing returns to scale and persistent profitability. It is not an unusual feature of our setup.[19] Sustained volatility in our setup plus that convex demand guarantees *some* firms will become highly profitable, invest, and grow, as Chang et al. (2024) document about industries with high asset volatility. That dynamic creates tension in our model, because high volatility is a feature of low- and middle-income

[19]For example, in a simple frictionless version of our model, managers set the cost of capital $r + \delta$ equal to the expected marginal product of capital tomorrow $A\widetilde{\mathbf{E}}[z']k'^{\alpha-1}$. That means $k' = [\frac{A}{r+\delta}]^{1/(1-\alpha)} \exp[\frac{\rho \log(z)+\sigma^2/2}{1-\alpha}]$, which is convex in $\log(z)$ while $\rho > 0$ and $\alpha \in (0, 1)$.

countries. High cash flow volatility should lead to investment and growth opportunities, but that is at odds with those countries' low GDP per capita. Our calibration resolves this tension by giving them low TFP residuals that counter the volatility effect, depressing investment and output. The result is a positive but modest slope between capital-output ratios and economic development when fitting the model to poor countries' high volatility.

The right panel of Figure 6 shows managerial demand for capital on a logarithmic vertical scale and reveals the effects of overprecision. Because it means that managers underestimate the amount of volatility the firm is subject to, overprecision leads them to *undervalue* the real (call and put) options that let them delay investment decisions and reconsider them in the future (Abel and Eberly, 1996; Abel et al., 1996; Bloom et al., 2007; Bloom et al., 2007; Baker et al., 2024). Overprecise managers, thus, have a demand function with a smaller flat region of inaction than rational managers (compare the curves for $\tilde{\sigma} = 0.17$ and $\sigma = 0.44$ in the figure). They start reselling capital (and paying the resale loss γ) sooner after a drop in profitability, and start investing sooner after an increase.

A higher sensitivity of investment to profitability when managers are overprecise tends reallocate capital towards profitable enterprises and away from unprofitable ones, as Barrero (2022) notes. That boost to reallocation raises GDP per capita even while holding TFP and the aggregate capital stock constant, lowering the capital-output (K/Y) ratio.[20] In our full calibration, high overprecision and the associated boost to reallocation in rich countries also helps explain why they are rich. Thus, overprecision tends to close cross-country TFP gaps in our full calibration, as Figure 5b shows.

Overall, overprecision yields lower demand for capital at very high and very low levels of profitability $\log(z)$, as revealed by the right panel of Figure 5b. The solid curve is below the dashed curve at the far right and left of the figure. Much of this effect comes from overprecise managers reallocating capital away swiftly from unprofitable enterprises, whereas rational managers would hold on to that capital for the option value of keeping it. A similar logic depresses investment under high profitability, since managers underestimate the firm's future growth options and therefore underinvest. When combined with poor and middle-income countries' high volatility, this underinvestment lowers capital-output ratios in the developing world. The result is that the slope between capital-output ratios and log(GDP per capita) in Figure 5a doubles when we include overprecision as a target in our calibration.

[20] Time-to-build, adjustment costs, and financial frictions in our model generate dispersion in the marginal product of capital and static misallocation as in Hsieh and Klenow (2009). Other things equal, that dispersion rises with volatility in our model as in Asker et al. (2014). But the absence of permanent and correlated distortions (see Bento and Restuccia, 2017 and David and Venkateswaran, 2019) limit the scope of static misallocation in our model.

The degree of overprecision matters too. If we give managers in middle- and low-income countries the stronger degree of overprecision we find in high-income ones, holding other parameters constant, the slope of the capital-output ratio gradient rises to 0.73, compared with about 0.63 in the data. Thus, poor-country managers being relatively more attuned to the (high) amount of volatility in their environment leads to less underinvestment and raises their countries capital-output ratio.

5.4 Robustness

How do our conclusions about capital-output ratios and TFP gaps across poor and rich countries depend on the specification of our model? Table 8 shows how they change across seven specifications that introduce additional frictions or weaken key mechanisms. Because our framework is simple (it only has two state variables and one control variable) and our quantitative exercises seek an exactly-identified mapping between parameters and moments, it is inexpensive to consider additional specifications.

Columns 3 to 5 of Table 8 report the slope between capital-output ratios and log(GDP per capita) in the full model calibration (matching columns 2 to 4 of Table 5); when we fit differences volatility and ignore overprecision; and when we ignore our facts altogether (targeting the volatility and common shocks of the high-income economy with no overprecision). Columns 6 to 8 show the percent change in relative TFP when fitting the full model versus ignoring our facts . Row (1) shows our baseline specification, reporting the slope estimates from Figure 5a and relative TFP $\hat{A}$ differences between Tables 7c and 7a. See the notes for Table 8 and the appendix for more details the other specifications.

The second to fifth rows of Table 8 reveal similar quantitative implications of our facts for cross-country investment and productivity. In each case, we obtain a positive slope between capital-output ratios and log(GDP per capita) ranging from 0.6 to 0.8 when matching our facts – similar to the data. We also infer larger TFP gaps for developing and emerging economies (i.e., lower TFP) when matching our facts. The specification in row 2 yields the most conservative impact on residual TFP gaps: 15% smaller for the country with relative GDP per capita of 0.08, compared to 48% in the baseline. Row 2 also attributes a smaller role to overprecision in explaining the positive slope between capital-output ratios and log(GDP per capita). In rows 1 and 3 to 5 the slope drops by one- to two-thirds between the full model calibration and ignoring overprecision. But in row 2, the slope drops just one-seventh when we ignore overprecision.

The bottom two rows of Table 8 show how our ability to match the positive slope between capital-output ratios and log(GDP per capita) relies on two key parameters from Table 6. The first is the partial irreversibility of investment, which creates real options in

Table 8: **Model Robustness: Implications of Uncertainty & Volatility Facts**

		Slope: (K/Y) vs. log(GDP/person)			Δ TFP Residual (%) by Relative GDP/Person		
		Full	Country	Uniform			
Model	**Description of Specification**	**Model**	**Volatility**	**Volatility**	**0.50**	**0.23**	**0.08**
(1)	Baseline (Tab. 5, 6, 7, Fig. 5)	0.7	0.4	0.0	-9.9	-24.8	-48.1
(2)	Adjust for Jensen's effect on z	0.7	0.6	0.0	-2.2	-7.0	-14.9
(3)	No common shocks ($\mathcal{A}' = 0$)	0.8	0.5	0.0	-11.5	-31.8	-64.1
(4)	No external finance ($\psi = \infty$)	0.8	0.3	0.0	-6.4	-16.2	-35.2
(5)	With endogenous entry/exit	0.6	0.3	0.0	-12.2	-28.0	-46.4
(6)	Frictionless investment ($\gamma = 0$)	-0.1	0.0	0.0	-37.3	-41.4	-55.4
(7)	Less persistent z ($\rho = 0.8$)	0.4	0.1	0.0	-3.9	-9.9	-21.4

Notes: For each hypothetical country with relative GDP per capita of 0.50, 0.23, and 0.08, we report the difference in relative TFP $\hat{A}$ between our full model calibration that matches all of our facts about uncertainty and volatility (columns 2 to 4 of Table 5) and a calibration with no overprecision and uniform volatility and common shocks across all countries, at the level of the country with relative GDP per capita of 1.00. We also report the slope between aggregate capital-output K/Y ratios and log(GDP per capita) in the full and uniform volatility models. Row (1) reports results from our baseline specification with fixed parameters reported Table 6 and calibrated parameters in Table 7. Row (2) adjusts managerial expectations in each country downward by a factor of $\exp(-\tilde{\sigma}^2/2)$ and gross profit TFP A up by $\exp(\sigma^2/[2(1-\rho^2)])$ to remove any effects of high uncertainty or volatility on mean z' due to its log-Normality and Jensen's inequality. Row (3) sets all common shocks $\mathcal{A}'$ to zero and runs the calibration ignoring the evidence about forecast error bias and mean squared forecast errors from Figure 4b. Row (4) considers a specification of the model in which firms have no access to outside financing ($\psi = \infty$, in the extended model in the appendix). Row (5) allows for endogenous entry and exit (liquidation) dynamics by targeting an exit rate of 5% per period (10% per year) across all countries and allowing for a fixed cost f that creates operating leverage (see, e.g., Kochen, 2023, for evidence about exit rates across countries). Row (6) assumes no frictions to investment other than a one period time-to-build constraint ($\gamma = 0$) and adjusts managerial expectations of future z upward by a factor of $\exp(\sigma^2/2 - \tilde{\sigma}^2/2)$ since volatility enters the first-order-condition for optimal investment directly. Finally, row (7) uses the baseline parameterization but lowers the persistence of $\log(z)$ to 0.8 per period.

managers' investment problem. Eliminating that irreversibility by setting $\gamma = 0$ in the sixth row, our model is unable to generate higher capital-output ratios at higher GDP per capita in any of the calibrations. The second key parameter is the persistence of the profitability process. Indeed, the convexity of managerial investment demand from Figure 6 and thus strength of volatility (Oi-Hartman-Abel) effects rely on persistence. A positive shift in profitability creates no investment incentives if it is completely transitory. Assuming lower persistence of $\log(z)$ in the bottom row, thus, yields a flatter relationship between capital-output ratios and log(GDP per capita), and smaller changes to implied TFP gaps.

6. Discussion

Our paper provides a new explanation for the long-standing observation that that firms in poor countries invest less than rich ones (see, e.g., Mankiw et al., 1992, Hsieh and Klenow, 2010, and Caselli, 2005). The combination of irreversible investment, high cash flow volatility, and overprecision (whereby managers underestimate that volatility) jointly generate capital-output ratios that rise with GDP per capita in our model. Moreover,

distortions to managerial beliefs play a key role. Without overprecision our model still generates an upward-sloping relationship – but it is half as large as in the data. This finding makes our paper complementary to recent work about the importance of uncertainty, volatility, and overprecision over the business cycle, such as Bianchi et al. (2024).

We fit capital-output ratios in rich and poor countries without appealing directly to frictions that constrain investment in poor countries but not rich ones. Instead, the TFP shifters in our framework act as a catch-all residual for relative GDP per capita conditional on uncertainty and volatility. We infer lower TFP in developing/emerging economies to explain why poor-country managers don't invest and accumulate capital even though their countries' high volatility brings investment opportunities to a few lucky firms. Those low TFP shifters say there are strong economic forces that constrain investment in poor countries but not rich ones, and which are distinct from high uncertainty and volatility.

A key limitation of our paper is that it cannot identify the frictions or fundamentals behind those TFP residuals. Filling that gap, by quantifying and pinning down the forces that hold back poor countries' investment and productivity should be a priority of future research. They might include financial factors, such as a high opportunity cost of capital in poor countries (see, e.g., David et al., 2014 and Falk et al., 2018), weak financial markets, or frictions to capital reallocation of the sort that are cyclical in rich countries (e.g. Eisfeldt and Rampini (2006)). Indeed, Vereshchagina (2022) shows how lack of access to outside finance can also compound the negative effects of high uncertainty on investment and productivity. Our paper goes beyond hers by showing that overprecision is key to accounting for poor countries' lack of investment.

Non financial factors might also be behind our TFP residuals. If poor-country firms have lower returns to scale, for example due to delegation constraints, that will restrain investment (see, e.g., Akcigit et al., 2021) even if volatility creates growth opportunities. So might other distortions that generate misallocation and are canonically more severe in poor countries (see, e.g., Hsieh and Klenow, 2009, Bartelsman et al., 2013, Bento and Restuccia, 2017, Ayerst et al., 2024). Low TFP might even reflect a high domestic relative price of investment goods, which Hsieh and Klenow (2010) offer as an explanation for poor countries' lack of investment. Altogether, we conclude that managerial uncertainty and cash flow volatility interact with those fundamentals – whatever they might be.

Our model and data do help us rule out some channels that would explain low investment in poor countries. Volatile but transitory cash flow shocks would imply limited investment opportunities in such places. But the seventh row of Table 8 shows this story is hard to square with poor-countries' low capital-output ratios. Alternatively, if profitability shocks were more negatively skewed in poor countries, that would generate high volatility

and few investment opportunities. But we find little evidence of negative skewness in our data. Figure A.8 in the appendix shows average forecast errors are about flat with GDP per capita, and there is little correlation between the mean and variance of forecast errors. The same goes for managers' subjective skewness and the skewness of their forecast errors in Figure A.9. Altogether, this evidence suggests that skewness is not a latent driver of high volatility and limited investment in the developing world.

A long literature following Bloom (2009) and Fernández-Villaverde et al. (2011), among others, suggests that uncertainty is bad for economic outcomes. The real options mechanism that often underlies that result, central to the debate in Bachmann and Bayer (2013), is fully at play in our paper. That said, our focus is on the long-term effects of uncertainty and volatility, where Oi-Hartman-Abel effects are typically stronger. As Bloom (2014) notes, sustained long-run volatility is what guarantees *some* firms receive highly profitable investment opportunities in our model, as in Chang et al. (2024), and leads us to infer low TFP shifters that depress investment in poor countries. This parallels the finding in Bloom (2009) and Bloom et al. (2018) that recessions need a negative shock to average profitability, in addition to a volatility shock, to generate sustained downturns.

7. Concluding remarks

Our paper makes two key contributions to the literature on business uncertainty, volatility, and their impact on cross-country investment and output.

First, we document new facts about uncertainty in high- and low-volatility environments using surveys of over 31,000 managers across 41 countries. We show subjective uncertainty about future sales and realized sales volatility both decline with GDP per capita. Relative to prior work, we establish this pattern from a new perspective: from managers' viewpoints and information sets. Our data also lets us go further, showing that managers systematically underestimate volatility (they are *overprecise*), and more so in low-volatility rich countries. That means rich-country managers tune out a larger share of the little volatility their firms are exposed to. One of our key empirical contributions is to establish the global prevalence of overprecision and its gradient with GDP per capita.

Second, we build a dynamic model with heterogeneous firms and real investment options to quantify the implications of our facts. We calibrate high- and low-income economies using our cross-country evidence and ask: how much do differences in uncertainty and volatility matter for cross-country investment and output? We find our facts rationalize the upward-sloping relationship between aggregate capital-output ratios and GDP per capita. Managerial overprecision and its gradient across rich and poor countries accounts for about half of that positive gradient, while differences in volatility account for

the other half. If we instead calibrate the model to match GDP per capita gaps and abstract from our evidence on uncertainty and volatility, we obtain a flat relationship.

Our success at matching cross-country patterns in capital-output ratios does not come for free. Matching our facts about uncertainty and volatility leads our model to infer wider TFP gaps between rich and poor countries. Combined with high volatility and modest overprecision, that low TFP delivers low capital-output ratios in line with aggregate data. Thus, our residual TFP shifters stand in for mechanisms and forces that restrain investment in volatile poor countries but not stable rich ones. We cannot identify those forces, but our quantitative results suggest they interact with managerial overprecision to generate low capital-output ratios. Thus, our paper points to managerial decisions and capital budgeting as a central piece of the puzzle of why poor countries seem to invest too little and thereby remain poor.

References

ABEL, A. B. (1983): "Optimal investment under uncertainty," *American Economic Review*, 73, 228–233.

ABEL, A. B., A. K. DIXIT, J. C. EBERLY, AND R. S. PINDYCK (1996): "Options, the value of capital, and investment," *Quarterly Journal of Economics*, 111, 753–777.

ABEL, A. B. AND J. C. EBERLY (1996): "Optimal investment with costly reversibility," *Review of Economic Studies*, 63, 581–593.

ACEMOGLU, D., S. JOHNSON, AND J. A. ROBINSON (2005): "Institutions as a fundamental cause of long-run growth," *Handbook of Economic Growth*, 1, 385–472.

AKCIGIT, U., H. ALP, AND M. PETERS (2021): "Lack of selection and limits to delegation: firm dynamics in developing countries," *American Economic Review*, 111, 231–275.

ALTI, A. AND P. C. TETLOCK (2014): "Biased beliefs, asset prices, and investment: A structural approach," *Journal of Finance*, 69, 325–361.

ALTIG, D., J. M. BARRERO, N. BLOOM, S. J. DAVIS, B. MEYER, AND N. PARKER (2022): "Surveying business uncertainty," *Journal of Econometrics*, 231, 282–303.

ANDRADE, P., O. COIBION, E. GAUTIER, AND Y. GORODNICHENKO (2021): "No firm is an island? how industry conditions shape firms' expectations," *Journal of Monetary Economics*.

APEDO-AMAH, M. C., B. AVDIU, M. C. XAVIER CIRERA, E. DAVIES, A. GROVER, L. IACOVONE, U. KILINC, D. MEDVEDEV, F. O. MADUKO, S. POUPAKIS, J. TORRES, AND T. T. TRAN (2020): "Businesses through the COVID-19 Shock: Firm-Level Evidence from Around the World," Policy Research Working Paper 9434, World Bank.

ASKER, J., A. COLLARD-WEXLER, AND J. DE LOECKER (2014): "Dynamic inputs and resource (mis) allocation," *Journal of Political Economy*, 122, 1013–1063.

ASRIYAN, V. AND A. KOHLHAS (2025): "The Macroeconomics of Data: Scale, Product Choice, and Pricing in the Information Age," .

AYERST, S., D. M. NGUYEN, AND D. RESTUCCIA (2024): "The micro and macro productivity of nations," Tech. rep., National Bureau of Economic Research.

BACHMANN, R. AND C. BAYER (2013): "'Wait-and-See'business cycles?" *Journal of Monetary Economics*, 60, 704–719.

BACHMANN, R., K. CARSTENSEN, S. LAUTENBACHER, AND M. SCHNEIDER (2024): "Uncertainty and change: Survey evidence of firms' subjective beliefs," *Stanford mimeo*.

BACHMANN, R., S. ELSTNER, AND E. R. SIMS (2013): "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5, 217–49.

BAKER, S. R., N. BLOOM, AND S. J. TERRY (2024): "Using disasters to estimate the impact of uncertainty," *Review of Economic Studies*, 91, 720–747.

BARRERO, J. M. (2022): "The micro and macro of managerial beliefs," *Journal of Financial Economics*, 143, 640–667.

BARTELSMAN, E., J. HALTIWANGER, AND S. SCARPETTA (2013): "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, 103, 305–34.

BEN-DAVID, I., J. R. GRAHAM, AND C. R. HARVEY (2013): "Managerial miscalibration," *Quarterly Journal of Economics*, 128, 1547–1584.

BENTO, P. AND D. RESTUCCIA (2017): "Misallocation, establishment size, and productivity," *American Economic Journal: Macroeconomics*, 9, 267–303.

BERNANKE, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98, 85–106.

BIANCHI, F., C. L. ILUT, AND H. SAIJO (2024): "Smooth Diagnostic Expectations," Tech. rep., National Bureau of Economic Research.

BILS, M., P. J. KLENOW, AND C. RUANE (2021): "Misallocation or mismeasurement?" *Journal of Monetary Economics*, 124, S39–S56.

BLOOM, N. (2009): "The impact of uncertainty shocks," *Econometrica*, 77, 623–685.

——— (2014): "Fluctuations in uncertainty," *Journal of Economic Perspectives*, 28, 153–76.

BLOOM, N., S. BOND, AND J. VAN REENEN (2007): "Uncertainty and investment dynamics," *Review of Economic Studies*, 74, 391–415.

BLOOM, N., S. J. DAVIS, L. FOSTER, B. LUCKING, S. OHLMACHER, AND I. SAPORTA-EKSTEN (2021): "Business-level expectations and uncertainty," Tech. rep., National Bureau of Economic Research.

BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. J. TERRY (2018): "Really uncertain business cycles," *Econometrica*, 86, 1031–1065.

BOLTON, P., M. K. BRUNNERMEIER, AND L. VELDKAMP (2013): "Leadership, coordination, and corporate culture," *Review of Economic Studies*, 80, 512–537.

BORDALO, P., N. GENNAIOLI, AND A. SHLEIFER (2018): "Diagnostic expectations and credit cycles," *Journal of Finance*, 73, 199–227.

BORN, B., Z. ENDERS, G. J. MÜLLER, AND K. NIEMANN (2023): "Firm expectations about production and prices: Facts, determinants, and effects," in *Handbook of Economic Expectations*, Elsevier, 355–383.

BOUTROS, M., I. BEN-DAVID, J. R. GRAHAM, C. R. HARVEY, AND J. W. PAYNE (2020): "The persistence of miscalibration," Tech. rep., National Bureau of Economic Research.

CASELLA, G. AND R. BERGER (2024): *Statistical inference*, CRC Press.

CASELLI, F. (2005): "Accounting for cross-country income differences," *Handbook of Economic Growth*, 1, 679–741.

CATTANEO, M. D., R. K. CRUMP, M. H. FARRELL, AND Y. FENG (2024): "On binscatter," *American Economic Review*, 114, 1488–1514.

CHANG, H., A. D'AVERNAS, AND A. L. EISFELDT (2024): "Bonds versus Equities: Information for Investment," *The Journal of Finance*, 79, 3893–3941.

CHAROENWONG, B., Y. KIMURA, A. KWAN, AND E. TAN (2024): "Capital budgeting, uncertainty, and misallocation," *Journal of Financial Economics*, 153, 103779.

COIBION, O., Y. GORODNICHENKO, AND T. ROPELE (2020): "Inflation expectations and firm decisions: New causal evidence," *Quarterly Journal of Economics*, 135, 165–219.

COOPER, R. W. AND J. C. HALTIWANGER (2006): "On the nature of capital adjustment costs," *Review of Economic Studies*, 73, 611–633.

CRANE, L. D., R. A. DECKER, A. FLAAEN, A. HAMINS-PUERTOLAS, AND C. KURZ (2022): "Business exit during the COVID-19 pandemic: Non-traditional measures in historical context," *Journal of Macroeconomics*, 72, 103419.

DAVID, J. M., E. HENRIKSEN, AND I. SIMONOVSKA (2014): *The risky capital of emerging markets*, National Bureau of Economic Research.

DAVID, J. M. AND V. VENKATESWARAN (2019): "The sources of capital misallocation," *American Economic Review*, 109, 2531–2567.

DAVIS, S. J., J. HALTIWANGER, R. JARMIN, J. MIRANDA, C. FOOTE, AND E. NAGYPAL (2006): "Volatility and dispersion in business growth rates: Publicly traded versus privately held firms [with comments and discussion]," *NBER Macroeconomics Annual*, 21, 107–179.

DAVIS, S. J., J. C. HALTIWANGER, S. SCHUH, ET AL. (1998): "Job creation and destruction," *MIT Press Books*, 1.

DONOVAN, K., J. LU, T. SCHOELLMAN, ET AL. (2018): "Labor market flows and development," in *2018 Meeting Papers, Society for Economic Dynamics*, vol. 976.

EISFELDT, A. L. AND C. M. KUHNEN (2013): "CEO turnover in a competitive assignment framework," *Journal of Financial Economics*, 109, 351–372.

EISFELDT, A. L. AND A. A. RAMPINI (2006): "Capital reallocation and liquidity," *Journal of Monetary Economics*, 53, 369–399.

FALK, A., A. BECKER, T. DOHMEN, B. ENKE, D. HUFFMAN, AND U. SUNDE (2018): "Global evidence on economic preferences," *Quarterly Journal of Economics*, 133, 1645–1692.

FEENSTRA, R. C., R. INKLAAR, AND M. P. TIMMER (2015): "The next generation of the Penn World Table," *American economic review*, 105, 3150–3182.

FERNÁNDEZ-VILLAVERDE, J., P. GUERRÓN-QUINTANA, J. F. RUBIO-RAMIREZ, AND M. URIBE (2011): "Risk matters: The real effects of volatility shocks," *American Economic Review*, 101, 2530–2561.

GENNAIOLI, N. AND A. SHLEIFER (2010): "What comes to mind," *Quarterly Journal of Economics*, 125, 1399–1433.

GLAESER, E. L., R. LA PORTA, F. LOPEZ-DE SILANES, AND A. SHLEIFER (2004): "Do institutions cause growth?" *Journal of Economic Growth*, 9, 271–303.

GRAHAM, J. R. (2022): "Presidential address: Corporate finance and reality," *Journal of Finance*, 77, 1975–2049.

GUISO, L. AND G. PARIGI (1999): "Investment and demand uncertainty," *Quarterly Journal of Economics*, 114, 185–227.

HALTIWANGER, J., S. SCARPETTA, AND H. SCHWEIGER (2008): "Assessing job flows across countries: the role of industry, firm size and regulations," Tech. rep., National Bureau of Economic Research.

HARTMAN, R. (1972): "The effects of price and cost uncertainty on investment," *Journal of Economic Theory*, 5, 258–266.

HSIEH, C.-T. AND P. J. KLENOW (2009): "Misallocation and manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124, 1403–1448.

——— (2010): "Development accounting," *American Economic Journal: Macroeconomics*, 2, 207–223.

——— (2014): "The life cycle of plants in India and Mexico," *Quarterly Journal of Economics*, 129, 1035–1084.

JURADO, K., S. C. LUDVIGSON, AND S. NG (2015): "Measuring uncertainty," *American Economic Review*, 105, 1177–1216.

KHAN, A. AND J. K. THOMAS (2008): "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 76, 395–436.

KOCHEN, F. (2022): "Finance over the life cycle of firms," *Unpublished manuscript*.

KOREN, M. AND S. TENREYRO (2007): "Volatility and development," *Quarterly Journal of Economics*, 122, 243–287.

KOŞAR, G. AND W. VAN DER KLAAUW (2023): "Workers' Perceptions of Earnings Growth and Employment Risk," *FRB of New York Staff Report*.

KOZENIAUSKAS, N. (2023): "What's Driving the Decline in Entrepreneurship?" *Unpublished paper.*

KUMAR, S., Y. GORODNICHENKO, AND O. COIBION (2023): "The effect of macroeconomic uncertainty on firm decisions," *Econometrica*, 91, 1297–1332.

LOCHSTOER, L. A. AND T. MUIR (2022): "Volatility expectations and returns," *Journal of Finance*, 77, 1055–1096.

MA, Y., T. ROPELE, D. SRAER, AND D. THESMAR (2020): "A quantitative analysis of distortions in managerial forecasts," Tech. rep., National Bureau of Economic Research.

MALMENDIER, U. AND G. TATE (2005): "Does overconfidence affect corporate investment? CEO overconfidence measures revisited," *European Financial Management*, 11, 649–659.

MANKIW, N. G., D. ROMER, AND D. N. WEIL (1992): "A contribution to the empirics of economic growth," *The quarterly journal of economics*, 107, 407–437.

MANSKI, C. F. (2004): "Measuring expectations," *Econometrica*, 72, 1329–1376.

MEYER, B., N. PARKER, AND X. SHENG (2021): "Unit Cost Expectations and Uncertainty: Firms' Perspectives on Inflation," .

MOSCOSO BOEDO, H. (2018): "New Facts About Firm Risk Across Countries And Over The Business Cycle," *Economic Inquiry*, 56, 510–529.

OI, W. Y. (1961): "The desirability of price instability under perfect competition," *Econometrica*, 58–64.

POSCHKE, M. (2014): "The firm size distribution across countries and skill-biased change in entrepreneurial technology," *IZA Discussion Paper*.

SALGADO, S. (2020): "Technical change and entrepreneurship," *Available at SSRN 3616568*.

VERESHCHAGINA, G. (2022): "Uncertainty, Firm Life-Cycle Growth, and Aggregate Productivity," Tech. rep., Mimeo.

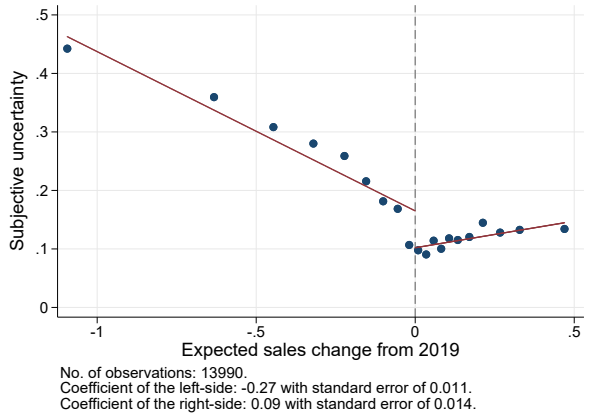
WEBER, M., B. CANDIA, H. AFROUZI, T. ROPELE, R. LLUBERAS, S. FRACHE, B. MEYER, S. KUMAR, Y. GORODNICHENKO, D. GEORGARAKOS, ET AL. (2025): "Tell Me Something I Don't Already Know: Learning in Low-and High-Inflation Settings," *Econometrica*, 93, 229–264.

Internet Appendix — Not Intended for Publication

A. Additional results

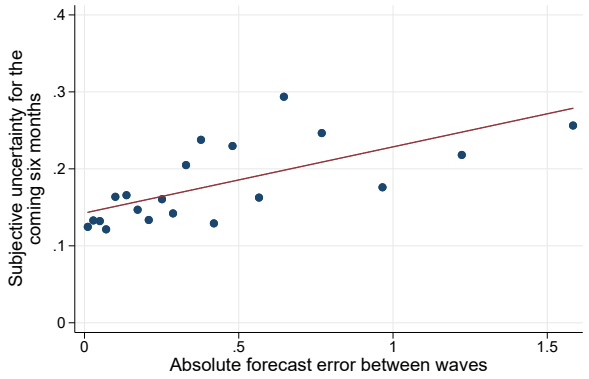
Figure A.1: **Uncertainty reflects shifts in the business environment.**

(a) Subjective uncertainty has a negative correlation with expected sales.



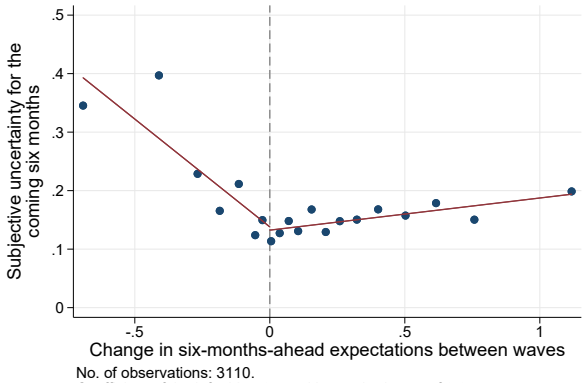
No. of observations: 13990.
Coefficient of the left-side: -0.27 with standard error of 0.011.
Coefficient of the right-side: 0.09 with standard error of 0.014.

(b) Uncertainty rises with past absolute forecast errors.



No. of observations: 4868.
Coefficient: 0.09 with standard error of 0.023.

(c) Uncertainty is v-shaped in revisions to expected sales.

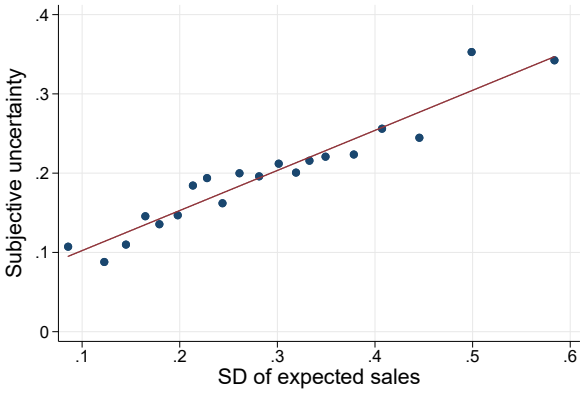


No. of observations: 3110.
Coefficient of the left-side: -0.37 with standard error of 0.057.
Coefficient of the right-side: 0.05 with standard error of 0.018.

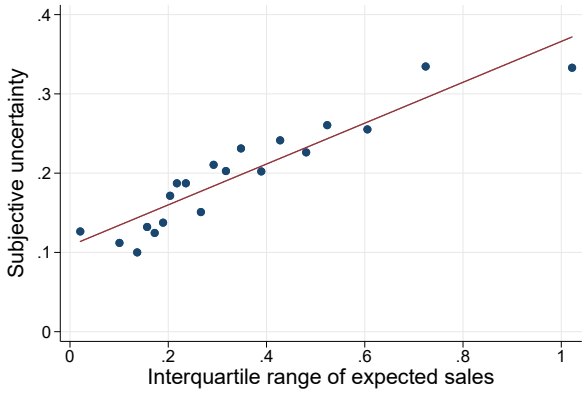
Notes: Panel a shows an employment-weighted binned scatter plot of firm-level subjective uncertainty against sales expectations pooling across all country-wave cross-sections. Panels b shows a binned scatter plot of subjective uncertainty about six-months-ahead sales as expressed in follow-up interviews on the vertical axis against the absolute error (i.e. difference) between forecast six-months-ahead sales in the initial interview and realized sales in the 30 days prior to the follow-up interview. Panels c shows a binned scatter plot of subjective uncertainty about six-months-ahead sales in the follow-up interview on the vertical axis against the change in expected sales between the initial and follow-up interviews on the horizontal axis. These relationships are computed using employment-weights. Sales expectations and uncertainty concern the next 6 months relative to the same period of 2019. The sample for panel a includes businesses from all countries and waves. Panels b and c focus on the balanced panel where we observe initial and follow-up interviews. The reported statistics below a figure correspond to the least squares regression in the underlying micro data and their corresponding robust standard error.

Figure A.2: **Country-sectors with Greater Dispersion in Expected Sales Also Have Higher Average Uncertainty about Future Sales**

(a) Standard deviation of expected sales growth.



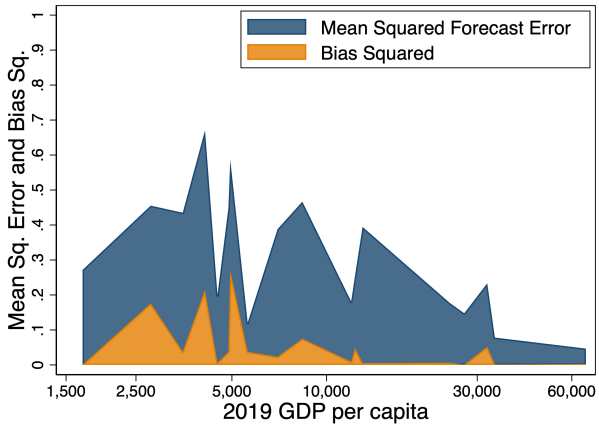
(b) Interquartile range of expected sales growth.



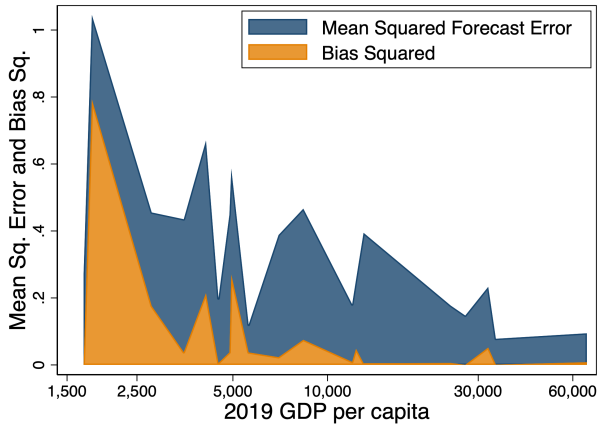
Notes: In each wave-country-sector we compute the standard deviation and the interquartile range of the expected sales growth for the next six months and the average subjective uncertainty about future sales growth. These computations use employment weights. Panel a shows the binned scatter plot for average uncertainty against the standard deviation of expected sales growth. Panel b uses the interquartile range on the x-axis as a measure of dispersion. Expected sales growth corresponds to the next 6 months relative to the same period of 2019. The reported statistics below each figure correspond to the least squares regression in the underlying micro data and the corresponding robust standard error.

Figure A.3: **Small Sample Bias is Only a Significant Contributor to Country-Level Mean Squared Forecast Errors in Sierra Leone.**

(a) Main Cross-Country Sample (Excl. Sierra Leone).



(b) All Countries (With Sierra Leone)

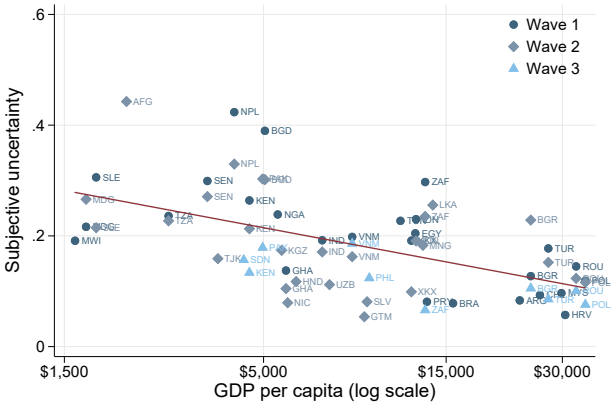


Notes: In both charts we plot the mean squared forecast error and bias squared by country against 2019 GDP per capita. The left chart uses our main sample that excludes Sierra Leone, while the right chart adds Sierra Leone. We compute absolute forecast errors as the absolute difference between realized sales in the 30 days prior to the follow-up interview and forecast sales from the initial interview. GDP per capita data are from 2019 and measured in 2019 US dollars at purchasing power parity rates. We obtain the bias squared by averaging across (non-absolute) forecast errors and then squaring the result.

Figure A.4: **Uncertainty and Volatility Decline with GDP per Capita**

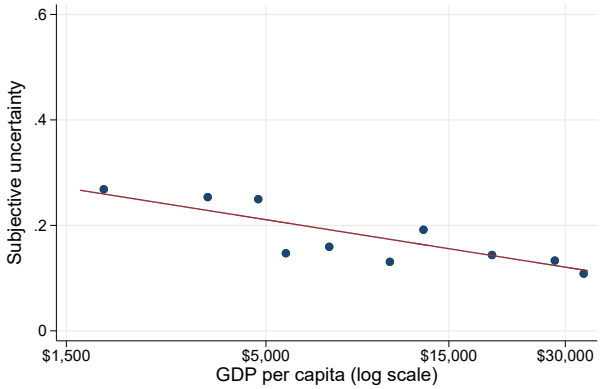
Uncertainty vs. GDP per Capita

(a) **Raw Country-Wave Cross Dection**



No. of observations: 27046.

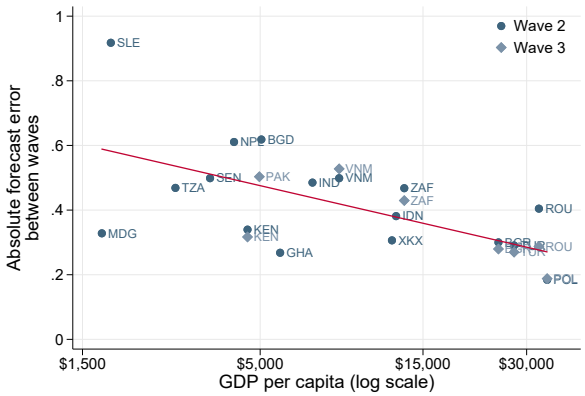
(b) **Controls for Firm Size, Sector, and Quarter**



No. of observations: 26734.
Coefficient: -0.05 with standard error of 0.001.

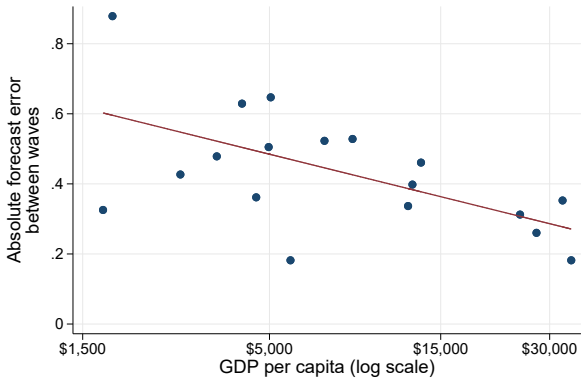
Volatility (Absolute Forecast Errors) vs. GDP per Capita

(c) **Raw Country-Wave Cross Section**



No. of observations: 4853.

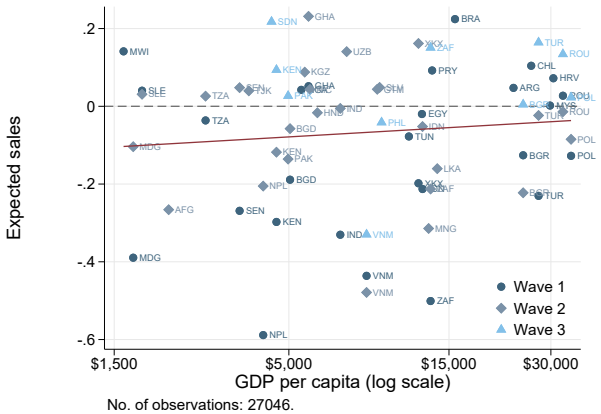
(d) **Controls for Firm Size, Sector, and Quarter**



No. of observations: 4819.
Coefficient: -0.11 with standard error of 0.007.

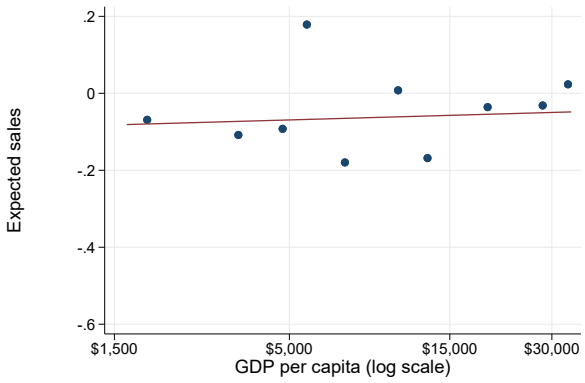
Expected Sales vs. GDP per Capita

(e) **Raw Country-Wave Cross Section**



No. of observations: 27046.

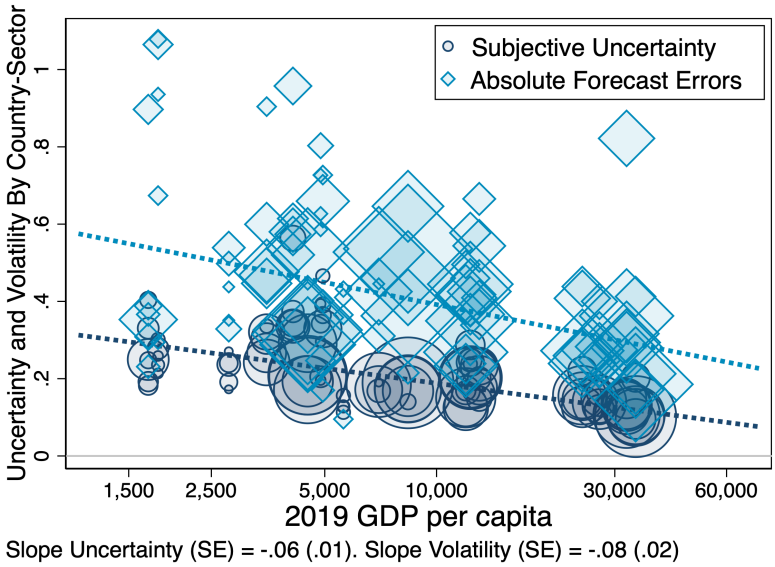
(f) **Controls for Firm Size, Sector, and Quarter**



No. of observations: 26734.
Coefficient: 0.02 with standard error of 0.003.

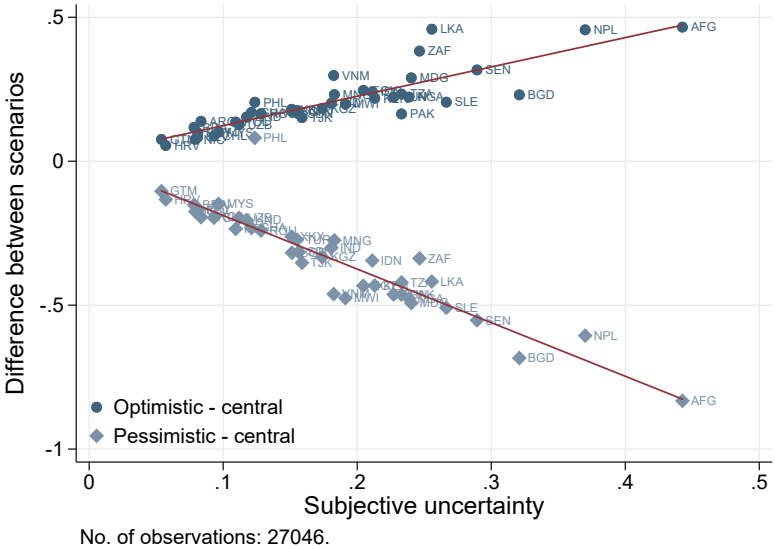
Notes: The vertical axis shows employment-weighted averages across firms by country-wave (left panels) and in the binned scatter plot (right panels). Panels (a) and (b) have subjective uncertainty about six-months-ahead sales on the vertical axis; panels (c) and (d) have volatility (absolute forecast errors); panels (e) and (f) have sales expectations. Sales changes are expressed relative to the same period in the prior year. We measure GDP per capita in 2019, using 2019 US dollars at purchasing power parity.

Figure A.5: **Country-Sector-Level Uncertainty and Volatility Decline with GDP per Capita**



Notes: We compute employment-weighted average uncertainty about six-months ahead sales, and average volatility (absolute forecast errors) across firms for 89 country-sectors and plot them against GDP per capita. The size of each marker reflects the number of forecast error observations by country-sector. Dotted lines show the fit line from regressions weighted by the number of forecast error observations by country-sector. We measure GDP per capita in 2019, using 2019 US dollars at purchasing power parity.

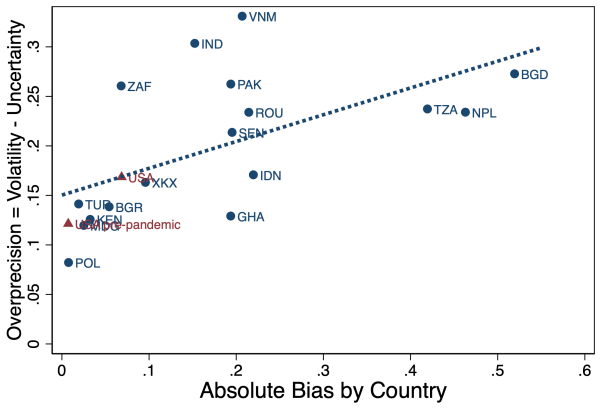
Figure A.6: **High Uncertainty Reflects Outward Shifts of Both the Optimistic and Pessimistic Scenarios**



Notes: For each country, we compute the employment-weighted average difference between the optimistic and central scenarios of managers' subjective distributions for six-months-ahead sales changes. We do the same for the pessimistic scenario, and plot both averages against average subjective uncertainty in the country.

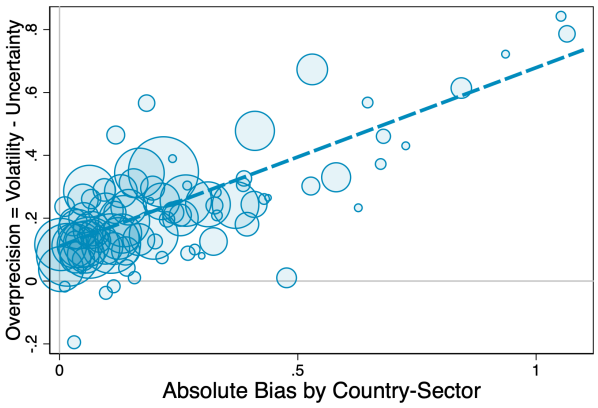
Figure A.7: **Overprecision Exists Even When Country-level Bias (Common Shocks) Are Near Zero**

(a) **Across Countries, Overprecision as a Difference**



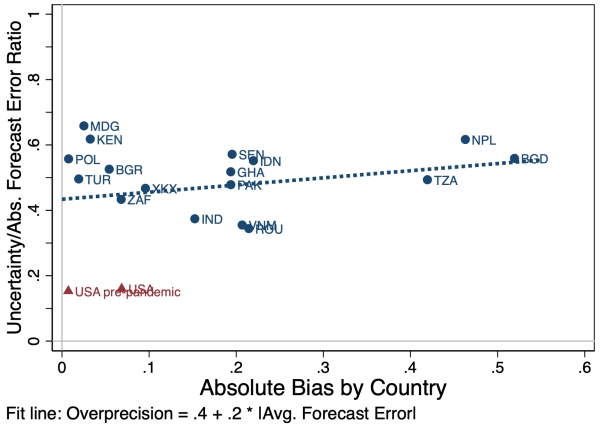
Fit line: Overprecision = .2 + .3 * |Avg. Forecast Error|

(b) **Across Country-Sectors, Overprecision as a Difference**



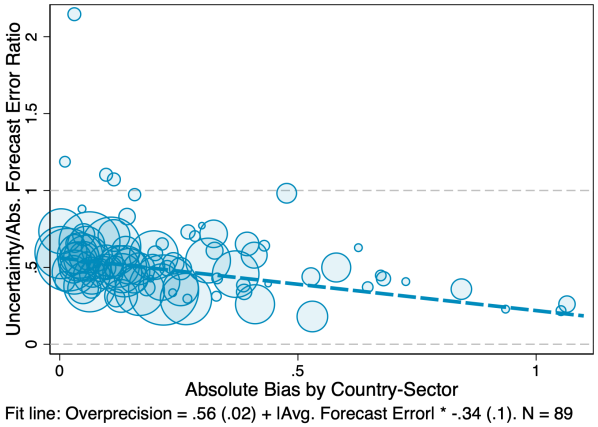
Fit line: Overprecision = .11 (.01) + |Avg. Forecast Error| * .57 (.08). N = 89

(c) **Across Countries, Overprecision as a Ratio**



Fit line: Overprecision = .4 + .2 * |Avg. Forecast Error|

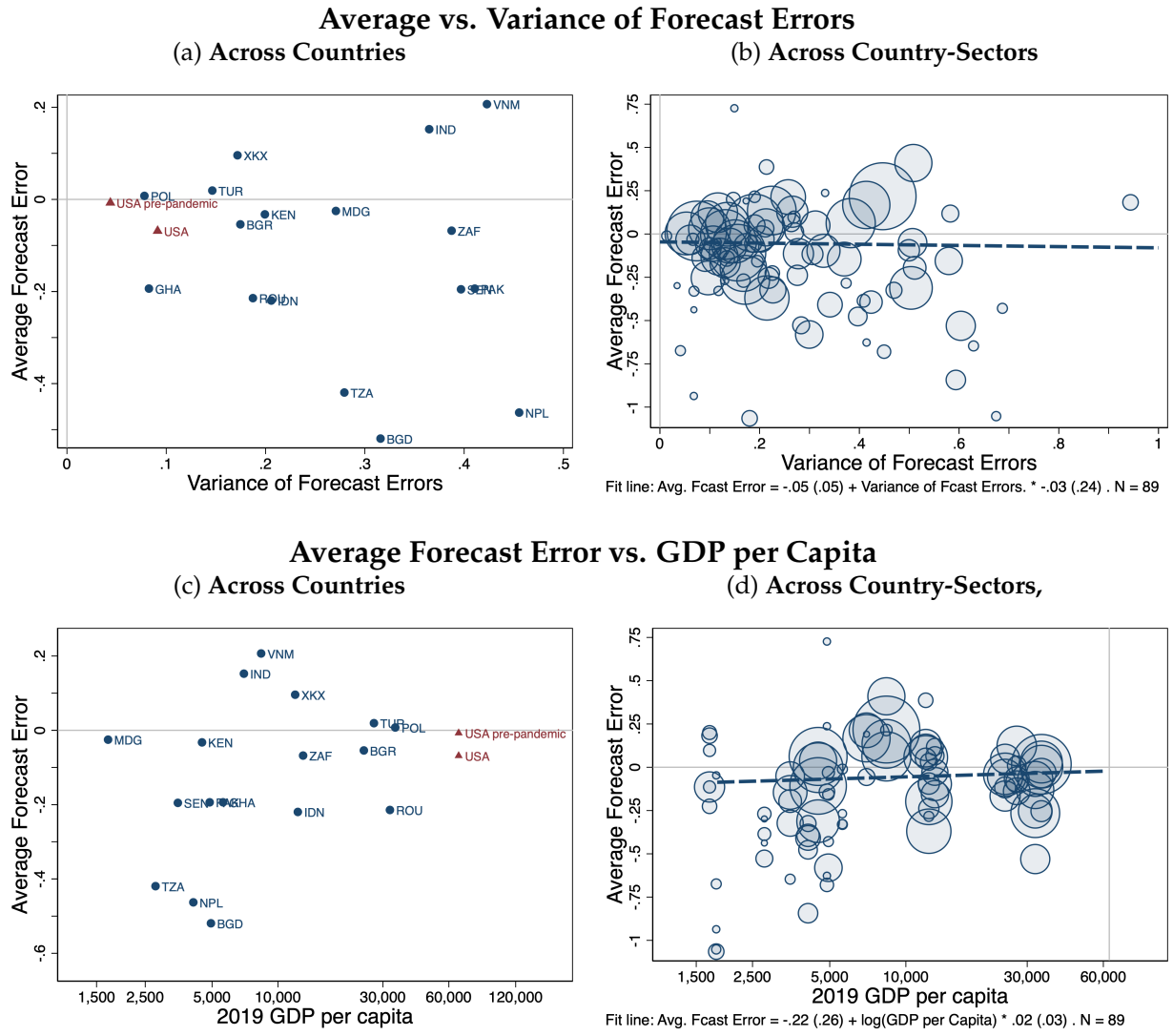
(d) **Across Country-Sectors, Overprecision as a Ratio**



Fit line: Overprecision = .56 (.02) + |Avg. Forecast Error| * -.34 (.1). N = 89

Notes: In each chart we plot a measure of overprecision against absolute bias (a measure of the common shock across firms). The charts on the left use country-level and those on the right country-sector-level averages. The top charts measure overprecision as the difference between average volatility (absolute forecast error) and subjective uncertainty. The bottom charts use the ratio of uncertainty to volatility.

Figure A.8: **Average Forecast Errors (Bias) Don't Correlate Strongly with Forecast Error Variance or GDP per Capita**

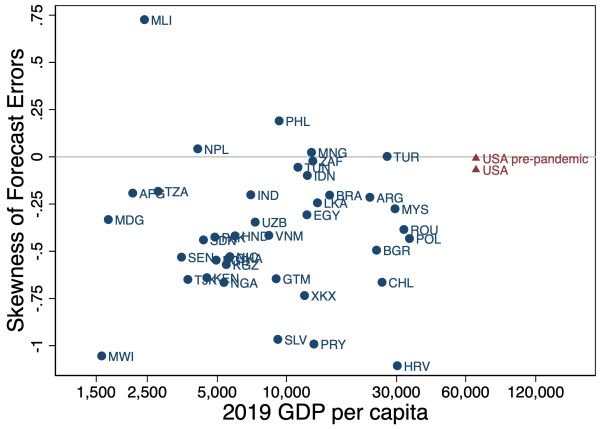


Notes: In the top panels, we compute employment-weighted averages and variances of forecast errors by country (left) and country-sector (right) and plot them against each other. In the bottom panels we plot average forecast errors against 2019 PPP GDP per capita by country (left) and country-sector (right).

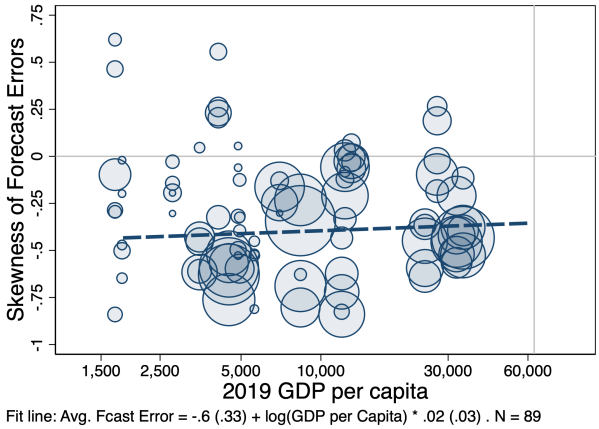
Figure A.9: **No Strong Evidence That Subjective or Realized Skewness Rises with GDP per Capita**

Subjective Skewness vs. GDP per Capita

(a) **Across Countries**



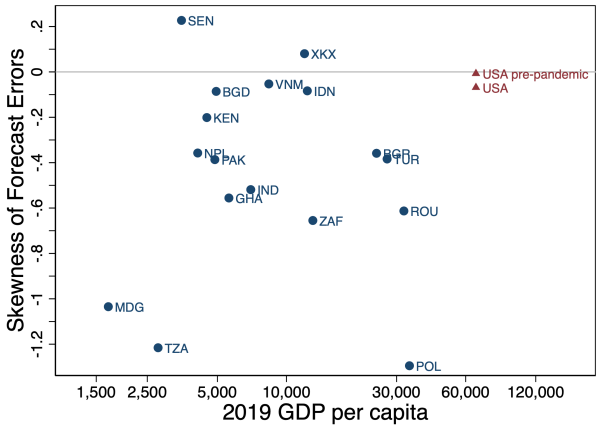
(b) **Across Country-Sectors,**



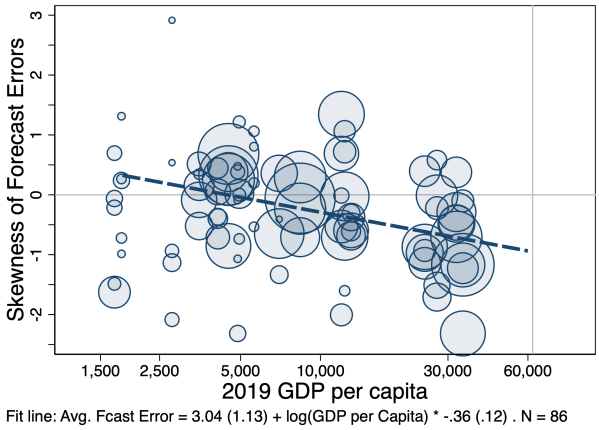
Fit line: Avg. Fcast Error = -.6 (.33) + log(GDP per Capita) * .02 (.03) . N = 89

Forecast Error Skewness vs. GDP per Capita

(c) **Across Countries**



(d) **Across Country-Sectors**

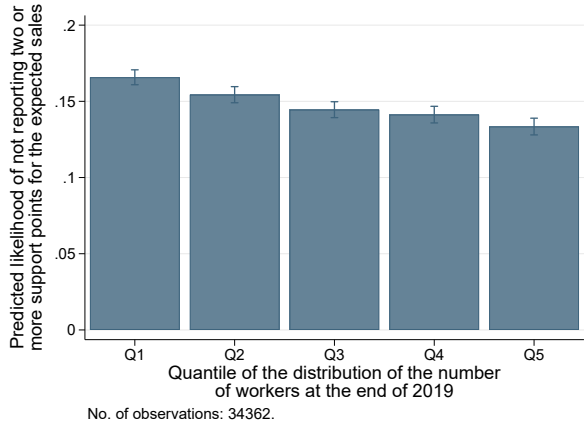


Fit line: Avg. Fcast Error = 3.04 (1.13) + log(GDP per Capita) * -.36 (.12) . N = 86

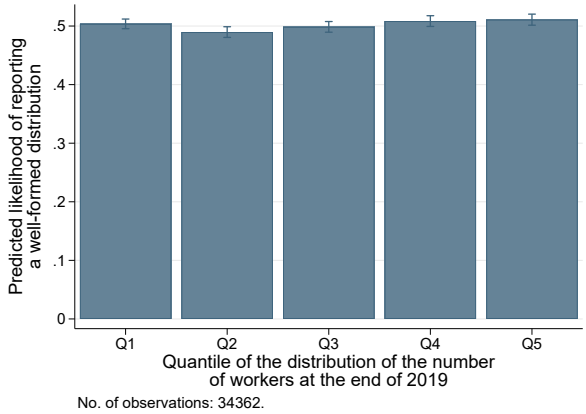
Notes: In the top panels, we compute employment-weighted averages forecast errors by country (left) and country-sector (right) and plot them against 2019 PPP GDP per capita. In the bottom panels we plot the average subjective skewness of managers' subjective distributions by country (left) and country-sector (right) and plot them against 2019 PPP GDP per capita.

Figure A.10: **The Likelihood of Providing Well-formed Subjective Distributions Increases with Firm Size**

(a) Average predicted likelihood of not reporting two or more support points for each quantile of the firm size distribution.



(b) Average predicted likelihood of reporting well-formed subjective distributions for each quantile of the firm size distribution.



Notes: In panel a the dependent variable is an indicator that equals 1 when the subjective distribution has two or more missing support points for the expected sales growth, and 0 otherwise. In panel b the dependent variable is an indicator that equals 1 when the firm reports a well-formed subjective distribution for sales in the coming six months. Explanatory variables in both cases are fixed effects for country, quarter, and country-wave-sector firm size quintiles (based on pre-pandemic employment). We pool data across country-waves and run least squares estimations for each dependent variable. In each case, the figures show the average predicted likelihood (the average of the linear prediction) at each size quintile, keeping the other regressors constant.

Figure A.11: **Firm Value is Convex in Profitability**

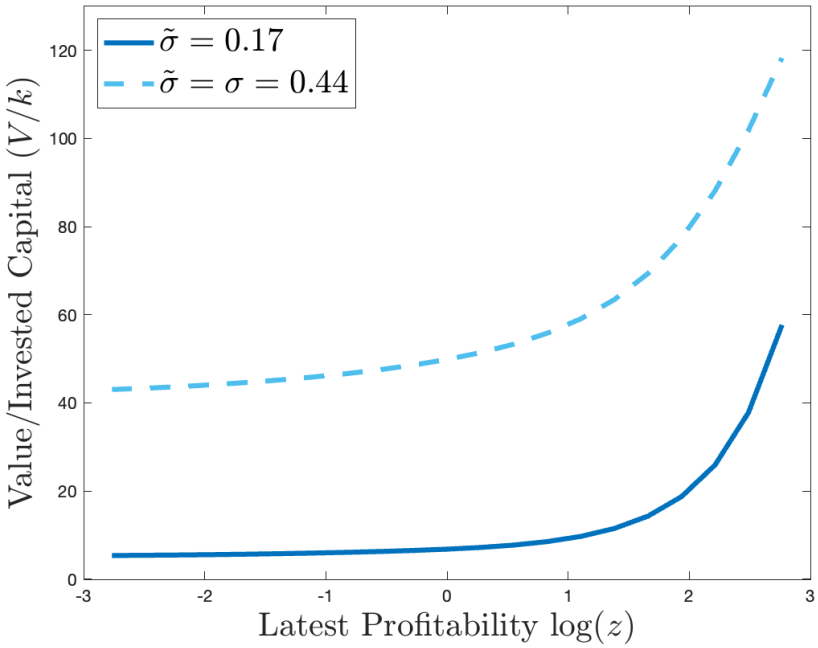


Table A.1: **Expectations and Uncertainty Correlate with Employment Outcomes and Plans**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change in employment last 30 days			**Expected change in employment**			**Employment uncertainty**	
Expected change in sales	0.036^{***}	0.026^{***}	0.011	0.613^{***}	0.564^{***}	0.566^{***}		
	(0.009)	(0.006)	(0.008)	(0.053)	(0.050)	(0.050)		
Sales uncertainty	-0.019^{+}	-0.025^{*}	-0.027^{*}	0.093	0.007	0.000	0.472^{***}	0.456^{***}
	(0.012)	(0.014)	(0.014)	(0.118)	(0.072)	(0.075)	(0.049)	(0.050)
Country x Sector FE	No	Yes	Yes	No	Yes	Yes	No	Yes
Quarter FE	No	No	Yes	No	No	Yes	No	Yes
Observations	19,543	19,542	18,590	6,694	6,694	6,595	6,694	6,595
R^2	0.010	0.078	0.100	0.427	0.579	0.582	0.285	0.345
Within R^2		0.006	0.002		0.411	0.413		0.255
No. of clusters	185	184	184	64	64	64	64	64

Notes: We compute changes in employment in the 30 days prior to the survey interview using data on current employment and survey questions about recent changes in employment, and express them as arc-changes. The table reports standard errors clustered by country-sector. $^{+}$ $p < 0.15$ * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: **Uncertainty Declines with GDP per Capita: Trust, Corruption, Women Leaders, and Exporters**

	(1)	(2)	(3)	(4)
	Subjective uncertainty			
GDP per capita (log)	-0.045^{***}	-0.028^{***}	-0.056^{***}	-0.033^{***}
	(0.010)	(0.009)	(0.007)	(0.006)
Absolute change in sales		0.080^{***}		0.097^{***}
		(0.010)		(0.008)
GDP SD 09-19 / Mean		1.403^{***}		0.594^{**}
		(0.254)		(0.248)
SD (arc) change in sales same country-wave-sector		0.030		0.087^{**}
		(0.039)		(0.036)
Exchange rate volatility last 30 days		0.184		0.629^{**}
		(0.176)		(0.280)
"People can be trusted (WVS)"	0.036	-0.061		
	(0.105)	(0.076)		
"There is corruption in my country (WVS)"	-0.009	0.016		
	(0.008)	(0.010)		
Women-led			-0.002	-0.002
			(0.005)	(0.005)
Exporter			-0.015	-0.007
			(0.012)	(0.009)
Exchange rate regime dummies	No	Yes	No	Yes
Mobility and size	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes
Observations	12,172	12,172	18,438	18,438
Within R^2	0.055	0.150	0.085	0.174
No. of clusters	96	91	166	166

Notes: The table shows linear regressions with subjective business uncertainty about six-months-ahead sales (relative to the same period in the prior year) as dependent variable. We measure GDP per capita in 2019 US dollars and at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in. SD (arc) change in sales is the standard deviation of changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. The indicators on trust and corruption are (unweighted) country averages from the World Values Survey. Trust is the share of people who reported "Most people can be trusted." Corruption is a 1 to 10 question where 1 corresponds to "There is no corruption in my country" and 10 is "There is abundant corruption in my country." *Mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. We report heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: **Expectations Show No Clear Relationship with GDP per Capita**

	(1)	(2)	(3)	(4)	(5)	(6)
			Expected growth rate			
GDP per capita (log)	0.011	−0.006	−0.014	−0.016	−0.017	−0.025
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.017)
Absolute change in sales		−0.170***	−0.171***	−0.166***	−0.176***	−0.176***
		(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
GDP SD 09-19 / Mean			−1.743***	−1.729***	−1.161**	−1.766***
			(0.594)	(0.590)	(0.520)	(0.533)
SD (arc) change in sales same country-wave-sector				−0.066	−0.137	−0.141
				(0.099)	(0.102)	(0.095)
Exchange rate volatility last 30 days					1.167*	0.499
					(0.625)	(0.577)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,734	25,892	25,892	25,892	24,859	24,859
Within R^2	0.007	0.065	0.081	0.082	0.092	0.101
No. of clusters	195	195	195	195	185	185

Notes: The table reports linear regressions with expected growth rate about six-months-ahead sales (relative to the same period in the prior year) as the dependent variable. We measure GDP per capita in 2019 US dollars at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in from 2009 to 2019. SD (arc) change in sales is the standard deviation of arc-changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. *Mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. We show heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: **Uncertainty Declines with GDP per Capita: Manufacturing Firms Only**

	(1)	(2)	(3)	(4)	(5)	(6)
			Subjective Uncertainty			
GDP per capita (log)	-0.050^{***}	-0.038^{***}	-0.034^{***}	-0.031^{***}	-0.031^{***}	-0.024^{***}
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Absolute change in sales		0.105^{***}	0.104^{***}	0.097^{***}	0.096^{***}	0.097^{***}
		(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
GDP SD 09-19 / Mean			0.636	0.609	0.675	0.966^{**}
			(0.430)	(0.419)	(0.485)	(0.438)
SD (arc) change in sales same country-wave-sector				0.099^{*}	0.093	0.062
				(0.058)	(0.073)	(0.075)
Exchange rate volatility last 30 days					0.478	1.322^{*}
					(0.521)	(0.701)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,400	8,170	8,170	8,170	7,752	7,752
Within R^2	0.071	0.143	0.152	0.155	0.153	0.163
No. of clusters	40	40	40	40	38	38

Notes: The table reports linear regressions with subjective business uncertainty about six-months-ahead sales (relative to the same period in the prior year) as the dependent variable. We measure GDP per capita in 2019 US dollars at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in from 2009 to 2019. SD (arc) change in sales is the standard deviation of arc-changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. *Mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. We show heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: **Uncertainty Declines with GDP per Capita: Firms with 20 to 99 Employees Only**

	(1)	(2)	(3)	(4)	(5)	(6)
			Subjective Uncertainty			
GDP per capita (log)	-0.056^{***}	-0.046^{***}	-0.044^{***}	-0.041^{***}	-0.041^{***}	-0.033^{***}
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Absolute change in sales		0.108^{***}	0.108^{***}	0.102^{***}	0.099^{***}	0.100^{***}
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
GDP SD 09-19 / Mean			0.307	0.293	0.312	0.618^{***}
			(0.256)	(0.243)	(0.244)	(0.204)
SD (arc) change in sales same country-wave-sector				0.078^{*}	0.072	0.072
				(0.043)	(0.045)	(0.044)
Exchange rate volatility last 30 days					0.097	0.916^{**}
					(0.275)	(0.376)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,187	8,903	8,903	8,899	8,599	8,599
Within R^2	0.078	0.158	0.160	0.165	0.162	0.176
No. of clusters	193	193	193	191	180	180

Notes: The table reports linear regressions with subjective business uncertainty about six-months-ahead sales (relative to the same period in the prior year) as the dependent variable. We measure GDP per capita in 2019 US dollars at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in from 2009 to 2019. SD (arc) change in sales is the standard deviation of arc-changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. *Mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. We show heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: **Uncertainty Declines with GDP per Capita: Firms Without Imputed Probability Vector**

	(1)	(2)	(3)	(4)	(5)	(6)
			Subjective Uncertainty			
GDP per capita (log)	-0.054^{***}	-0.045^{***}	-0.043^{***}	-0.040^{***}	-0.040^{***}	-0.036^{***}
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
Absolute change in sales		0.105^{***}	0.105^{***}	0.100^{***}	0.099^{***}	0.099^{***}
		(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
GDP SD 09-19 / Mean			0.385	0.348	0.376	0.772^{***}
			(0.273)	(0.269)	(0.269)	(0.249)
SD (arc) change in sales same country-wave-sector				0.077^{**}	0.078^{**}	0.093^{***}
				(0.034)	(0.034)	(0.034)
Exchange rate volatility last 30 days					0.533^{**}	1.001^{***}
					(0.240)	(0.326)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,900	18,337	18,337	18,332	17,948	17,948
Within R^2	0.065	0.136	0.139	0.141	0.143	0.154
No. of clusters	187	187	187	186	176	176

Notes: The table reports linear regressions with subjective business uncertainty about six-months-ahead sales (relative to the same period in the prior year) as the dependent variable. We measure GDP per capita in 2019 US dollars at purchasing power parity. Absolute change in sales is the absolute value of the sales level reported by each firm for the 30 days prior to the survey interview, expressed relative to the prior year. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in from 2009 to 2019. SD (arc) change in sales is the standard deviation of arc-changes in sales among firms in the same country, wave, and sector. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. *Mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. We show heteroskedasticity-robust standard errors, clustered by country-sector, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: **GDP per Capita and Subjective Uncertainty Independently Predict Absolute Forecast Errors: Manufacturing Firms Only**

	(1)	(2)	(3)	(4)	(5)	(6)
	Absolute Forecast Error					
GDP per capita (log)	-0.133^{***}	-0.106^{***}	-0.105^{***}	-0.105^{***}	-0.104^{***}	-0.085^{***}
	(0.039)	(0.030)	(0.031)	(0.032)	(0.030)	(0.021)
Uncertainty in previous wave (md)		0.443^{***}	0.444^{***}	0.448^{***}	0.439^{***}	0.423^{***}
		(0.121)	(0.121)	(0.122)	(0.115)	(0.104)
GDP SD 09-19 / Mean			0.817	0.962	0.369	0.286
			(1.358)	(1.259)	(1.426)	(1.554)
SD (arc) change in sales same country-wave-sector				-0.059	-0.056	-0.047
				(0.194)	(0.204)	(0.184)
Exchange rate volatility last 30 days					-1.734	-0.879
					(1.566)	(1.072)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,551	1,551	1,551	1,551	1,551	1,551
Within R^2	0.097	0.149	0.150	0.151	0.154	0.157
No. of clusters	18	18	18	18	18	18

Notes: The table shows firm-level linear regressions with firm volatility measured by absolute forecast errors about six-months-ahead sales (relative to the same period in the prior year). During a first interview, managers provide a subjective probability distribution for future sales which we use to measure expectations (i.e. forecasts) and subjective uncertainty. During a follow-up interview, they report sales levels in the past 30 days, relative to the prior year, and we measure forecast errors as the difference between these realized sales and the forecast from the first interview. We measure GDP per capita in 2019 US dollars and purchasing power parity. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. We report heteroskedasticity-robust standard errors, clustered at the country-sector level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: **GDP per Capita and Subjective Uncertainty Independently Predict Absolute Forecast Errors: Firms with 20 to 99 Employees Only**

	(1)	(2)	(3)	(4)	(5)	(6)
			Absolute Forecast Error			
GDP per capita (log)	-0.076^{***}	-0.062^{**}	-0.050^{**}	-0.032	-0.036^{*}	-0.055^{**}
	(0.027)	(0.028)	(0.024)	(0.021)	(0.020)	(0.022)
Uncertainty in previous wave (md)		0.234^{*}	0.256^{**}	0.087	0.075	0.070
		(0.119)	(0.119)	(0.122)	(0.122)	(0.129)
GDP SD 09-19 / Mean			2.800^{***}	2.411^{***}	1.711^{**}	0.404
			(0.952)	(0.766)	(0.794)	(1.160)
SD (arc) change in sales same country-wave-sector				0.521^{***}	0.528^{***}	0.477^{***}
				(0.123)	(0.124)	(0.128)
Exchange rate volatility last 30 days					-1.679^{***}	-1.345^{**}
					(0.610)	(0.514)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,295	1,295	1,295	1,289	1,289	1,289
Within R^2	0.044	0.057	0.074	0.118	0.123	0.134
No. of clusters	77	77	77	71	71	71

Notes: The table shows firm-level linear regressions with firm volatility measured by absolute forecast errors about six-months-ahead sales (relative to the same period in the prior year). During a first interview, managers provide a subjective probability distribution for future sales which we use to measure expectations (i.e. forecasts) and subjective uncertainty. During a follow-up interview, they report sales levels in the past 30 days, relative to the prior year, and we measure forecast errors as the difference between these realized sales and the forecast from the first interview. We measure GDP per capita in 2019 US dollars and purchasing power parity. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. We report heteroskedasticity-robust standard errors, clustered at the country-sector level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: **GDP per Capita and Subjective Uncertainty Independently Predict Absolute Forecast Errors: Firms Without Imputed Probability Vector**

	(1)	(2)	(3)	(4)	(5)	(6)
			Absolute Forecast Error			
GDP per capita (log)	-0.076^{***}	-0.062^{**}	-0.045^{**}	-0.026	-0.026	-0.035
	(0.025)	(0.025)	(0.022)	(0.020)	(0.020)	(0.024)
Uncertainty in previous wave (md)		0.399^{**}	0.417^{**}	0.315^{*}	0.315^{*}	0.285^{*}
		(0.175)	(0.171)	(0.158)	(0.158)	(0.160)
GDP SD 09-19 / Mean			2.866^{***}	2.882^{***}	2.872^{**}	2.810^{**}
			(1.068)	(0.875)	(1.209)	(1.312)
SD (arc) change in sales same country-wave-sector				0.084	0.085	0.098
				(0.109)	(0.111)	(0.116)
Exchange rate volatility last 30 days					-0.021	-1.632
					(1.464)	(1.314)
Exchange rate regime dummies	No	No	No	No	No	Yes
Mobility and size	Yes	Yes	Yes	Yes	Yes	Yes
Sector and quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,676	2,676	2,676	2,668	2,668	2,668
Within R^2	0.110	0.138	0.154	0.088	0.088	0.095
No. of clusters	62	62	62	55	55	55

Notes: The table shows firm-level linear regressions with firm volatility measured by absolute forecast errors about six-months-ahead sales (relative to the same period in the prior year). During a first interview, managers provide a subjective probability distribution for future sales which we use to measure expectations (i.e. forecasts) and subjective uncertainty. During a follow-up interview, they report sales levels in the past 30 days, relative to the prior year, and we measure forecast errors as the difference between these realized sales and the forecast from the first interview. We measure GDP per capita in 2019 US dollars and purchasing power parity. *GDP SD 09-19/Mean* is the coefficient of variation for GDP in the country a firm is located in. See Table B5 for exchange rate regimes, which we obtain from the 2020 IMF Annual Report on Exchange Arrangements and Exchange Restrictions. We report heteroskedasticity-robust standard errors, clustered at the country-sector level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: **Measures of Overprecision are Robust to Dropping Countries or Country-Sectors with High Bias Sq./MSE Ratios**

Average Gap Between Uncertainty & Abs. Forecast Errors						
	Across Countries			**Across Country-Sectors**		
	Difference	Ratio	N	Difference	Ratio	N
All	0.20 (0.02)	0.47 (0.03)	19	0.20 (0.01)	0.51 (0.02)	89
$\text{Bias}^2/\text{MSE} < 0.5$	0.20 (0.02)	0.47 (0.03)	19	0.19 (0.01)	0.51 (0.02)	78
$\text{Bias}^2/\text{MSE} < 0.4$	0.19 (0.02)	0.47 (0.03)	18	0.19 (0.01)	0.51 (0.02)	73
$\text{Bias}^2/\text{MSE} < 0.3$	0.19 (0.02)	0.45 (0.04)	15	0.19 (0.01)	0.51 (0.02)	65
$\text{Bias}^2/\text{MSE} < 0.2$	0.19 (0.02)	0.45 (0.04)	15	0.18 (0.01)	0.53 (0.02)	58
$\text{Bias}^2/\text{MSE} < 0.1$	0.19 (0.02)	0.45 (0.04)	13	0.18 (0.02)	0.52 (0.02)	42

Notes: We compute the mean gap between subjective uncertainty and absolute forecast errors across countries and across country-sectors in our data. We compute the gap as the difference (average absolute forecast error less average subjective uncertainty) or ratio (average absolute forecast error divided by average subjective uncertainty) and report the standard error of the cross-country or cross–country-sector mean. Each row focuses on a subsample defined by the ratio of the Bias Squared to Mean Squared Error at the country or country-sector level.

B. Additional information about the World Bank Group's Business Pulse Survey and Enterprise Survey

B.1 Description of data cleaning and preparation procedures

Given a survey response with subjective distribution for future sales, we impute probabilities and clean out that response using the following procedures:

- When a respondent provides the subjective probability for two or three support points and the sum of the probabilities is between 50 and 150 (but not exactly 100), we rescale the probabilities to add to 100.
- When a respondent provides three support points for the subjective distribution but some or all of the probabilities are missing, or the sum of the three probabilities is below 50 or above 150, we impute the probability vector using the sample of well-formed distributions. For each country-wave and each of the optimistic, central, and pessimistic scenarios, we compute the average probability for that scenario in the sample of distributions that have three support points and positive probabilities that add to 100. Then, we impute the full probability vector of the problematic distribution using the three scenario-specific average probabilities for the relevant country and wave.[21]
- When just one or two of the probabilities are missing we impute the missing ones using the corresponding country-wave-scenario average probability, and then rescale the firm's probability vector to add to 100.
- When a respondent fails to provide two or more support points we drop that observation from our analysis of subjective expectations and uncertainty. In such cases, we cannot obtain a non-degenerate distribution by modifying or imputing solely the probability vector.

See Table B4 for statistics on about the number of observations involved in these procedures.

[21] For Sierra Leone and Bangladesh, we use world averages to impute probabilities. The two survey waves conducted in Sierra Leone asked for the three support points but not the corresponding probabilities. In Bangladesh, there were not enough well-formed distributions in the sample to reliably use country-specific averages for the imputation.

Table B1: **Survey Coverage by Country and Time Period**

	2020			2021				2022
	Apr-Jun	Jul-Sep	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Jan-Mar
East Asia and Pacific								
Indonesia	X		X					
Malaysia			X					
Mongolia				X				
Philippines					X			
Vietnam		X	X	X				
Central and Eastern Europe								
Bulgaria	X		X		X			
Croatia					X			
Kosovo		X				X		
Kyrgyzstan					X			
Poland		X	X	X				
Romania	X			X	X			
Tajikistan						X		
Turkey		X		X				X
Uzbekistan						X		
Latin America								
Argentina						X		
Brazil		X						
Chile						X		
El Salvador				X				
Guatemala				X				
Honduras				X				
Nicaragua				X				
Paraguay						X		
North Africa								
Egypt							X	
Tunisia	X							
South Asia								
Afghanistan						X		
Bangladesh		X				X		
India	X					X		
Nepal	X					X		
Pakistan				X		X		
Sri Lanka						X		
Sub-Saharan Africa								
Ghana	X	X						
Kenya		X	X		X			
Madagascar		X		X				
Malawi			X					
Mali								
Nigeria		X						
Senegal	X			X				
Sierra Leone			X	X				
South Africa	X		X			X		
Sudan							X	
Tanzania		X	X					

Notes: Missing survey date for two waves: one in Ghana and one in Mali.

Table B2: **Number of Panel Observations by Country and Wave**

	No. of observations	Wave 1	Wave 2	Wave 3
Bangladesh	74	Jul-Sep 2020	Jul-Sep 2021	
Bulgaria	218	Apr-Jun 2020	Oct-Dec 2020	
	147		Oct-Dec 2020	Apr-Jun 2021
Ghana	21	Apr-Jun 2020	Jul-Sep 2020	
	40		Jul-Sep 2020	.
India	254	Apr-Jun 2020	Jul-Sep 2021	
Indonesia	357	Apr-Jun 2020	Oct-Dec 2020	
Kenya	429	Jul-Sep 2020	Oct-Dec 2020	
	390		Oct-Dec 2020	Apr-Jun 2021
Kosovo	310	Jul-Sep 2020	Jul-Sep 2021	
Madagascar	122	Jul-Sep 2020	Jan-Mar 2021	
Nepal	139	Apr-Jun 2020	Jul-Sep 2021	
Pakistan	36	Jan-Mar 2021	Jul-Sep 2021	
Poland	346	Jul-Sep 2020	Oct-Dec 2020	
	255		Oct-Dec 2020	Jan-Mar 2021
Romania	284	Apr-Jun 2020	Jan-Mar 2021	
	188		Jan-Mar 2021	Apr-Jun 2021
Senegal	227	Apr-Jun 2020	Jan-Mar 2021	
Sierra Leone	33	Oct-Dec 2020	Jan-Mar 2021	
South Africa	176	Apr-Jun 2020	Oct-Dec 2020	
	46		Oct-Dec 2020	Jul-Sep 2021
Tanzania	44	Jul-Sep 2020	Oct-Dec 2020	
Turkey	139	Jul-Sep 2020	Jan-Mar 2021	
	112		Jan-Mar 2021	Jan-Mar 2022
Vietnam	355	Jul-Sep 2020	Oct-Dec 2020	
	376		Oct-Dec 2020	Jan-Mar 2021

Table B3: **Sample Composition by Country-Wave**

	N	Percent of responses							
		Firm size (employees)			Sector				
		5 to 19	20 to 99	>100	Manufacturing	Retail	Hospitality	Services	Other
Indonesia									
Apr-Jun 2020	523	40.7	35.6	23.7	41.0	2.4	9.0	40.0	7.6
Oct-Dec 2020	429	40.3	32.2	27.5	40.5	3.2	7.4	39.6	9.3
Malaysia									
Oct-Dec 2020	632	22.0	27.1	50.9	26.0	23.0	4.1	32.3	14.6
Mongolia									
Jan-Mar 2021	199	39.7	46.7	13.6	30.7	37.7	4.0	6.0	21.6
Philippines									
Apr-Jun 2021	342	64.0	24.9	11.1	17.2	15.7	20.1	29.3	17.8
Vietnam									
Jul-Sep 2020	413	47.2	30.8	22.0	41.2	21.5	0.0	24.0	13.3
Oct-Dec 2020	417	52.0	28.8	19.2	41.0	23.2	0.0	23.5	12.3
Jan-Mar 2021	427	50.8	27.6	21.5	41.8	22.5	0.0	22.5	13.3
Bulgaria									
Apr-Jun 2020	572	49.5	36.9	13.6	32.2	20.6	6.8	23.6	16.8
Oct-Dec 2020	459	52.5	37.3	10.2	29.8	17.4	7.4	26.6	18.7
Apr-Jun 2021	360	53.3	36.1	10.6	24.7	18.3	5.6	33.3	18.1
Croatia									
Apr-Jun 2021	193	34.2	44.0	21.8	29.0	19.2	8.3	28.5	15.0
Kosovo									
Jul-Sep 2020	574	74.0	22.3	3.7	18.1	19.7	9.9	5.1	47.2
Jul-Sep 2021	454	74.9	21.6	3.5	18.7	24.4	8.8	4.8	43.2
Kyrgyzstan									
Apr-Jun 2021	376	67.0	29.3	3.7	34.8	19.7	8.2	13.6	23.7
Poland									
Jul-Sep 2020	802	32.8	47.3	20.0	37.8	24.2	3.5	22.1	12.5
Oct-Dec 2020	402	34.6	48.0	17.4	42.5	22.6	4.7	19.2	10.9
Jan-Mar 2021	328	37.5	43.9	18.6	43.4	23.2	4.0	19.3	10.1

Table B3: **Sample Composition by Country-Wave**

	N	Percent of responses							
		Firm size (employees)			Sector				
		5 to 19	20 to 99	>100	Manufacturing	Retail	Hospitality	Services	Other
Romania									
Apr-Jun 2020	549	41.3	44.4	14.2	21.1	16.4	12.2	32.8	17.5
Jan-Mar 2021	371	47.4	41.5	11.1	20.2	15.4	11.6	35.3	17.5
Apr-Jun 2021	317	46.1	42.0	12.0	24.0	17.6	12.1	30.7	15.7
Tajikistan									
Jul-Sep 2021	442	66.3	33.7	0.0	20.6	28.3	3.2	15.8	32.1
Turkey									
Jul-Sep 2020	628	40.8	39.5	19.7	45.1	9.7	5.3	24.7	15.2
Jan-Mar 2021	819	47.7	36.4	15.9	25.4	9.3	16.6	25.6	23.1
Jan-Mar 2022	188	46.8	37.2	16.0	21.8	10.6	16.5	28.2	22.9
Uzbekistan									
Jul-Sep 2021	448	60.7	39.3	0.0	22.5	25.9	7.1	20.8	23.7
Argentina									
Jul-Sep 2021	592	47.8	38.3	13.9	49.2	26.4	0.0	24.5	0.0
Brazil									
Jul-Sep 2020	327	28.7	38.2	33.0	45.8	21.6	4.4	5.3	22.9
Chile									
Jul-Sep 2021	448	70.3	22.8	6.9	15.0	33.7	16.5	34.8	0.0
El Salvador									
Jan-Mar 2021	305	39.0	35.4	25.6	48.2	33.3	2.3	13.5	2.6
Guatemala									
Jan-Mar 2021	149	38.9	35.6	25.5	38.8	34.7	5.4	15.6	5.4
Honduras									
Jan-Mar 2021	116	39.7	40.5	19.8	23.3	46.6	2.6	22.4	5.2
Nicaragua									
Jan-Mar 2021	135	40.0	45.9	14.1	31.3	33.6	10.4	22.4	2.2

Table B3: **Sample Composition by Country-Wave**

	N	Percent of responses							
		Firm size (employees)			Sector				
		5 to 19	20 to 99	>100	Manufacturing	Retail	Hospitality	Services	Other
Paraguay									
Jul-Sep 2021	150	62.0	27.3	10.7	23.3	20.7	8.0	48.0	0.0
Egypt									
Oct-Dec 2021	590	76.1	21.4	2.5	46.7	21.1	15.6	12.3	4.3
Tunisia									
Apr-Jun 2020	439	22.3	28.9	48.7	54.9	12.5	7.5	19.8	5.2
Afghanistan									
Jul-Sep 2021	454	62.3	30.0	7.7	43.2	6.5	4.8	8.7	36.8
Bangladesh									
Jul-Sep 2020	172	66.9	27.3	5.8	67.4	2.9	8.7	5.8	15.1
Jul-Sep 2021	394	60.7	28.7	10.7	80.2	4.1	4.8	4.8	6.1
India									
Apr-Jun 2020	571	23.6	43.6	32.7	62.1	0.9	0.9	29.6	6.5
Jul-Sep 2021	2051	41.9	48.1	10.0	40.6	19.9	13.5	23.0	2.9
Nepal									
Apr-Jun 2020	288	71.5	21.9	6.6	18.1	37.5	18.1	13.9	12.5
Jul-Sep 2021	387	74.4	18.3	7.2	33.9	23.3	14.2	14.0	14.7
Pakistan									
Jan-Mar 2021	195	58.5	26.2	15.4	15.4	8.2	27.7	43.1	5.6
Jul-Sep 2021	286	61.2	26.2	12.6	17.8	4.2	18.5	53.1	6.3
Sri Lanka									
Jul-Sep 2021	320	59.4	15.3	25.3	56.3	15.9	7.2	11.6	9.1
Ghana									
Apr-Jun 2020	47	0.0	59.6	40.4	19.1	14.9	4.3	31.9	29.8
Jul-Sep 2020	72	0.0	69.4	30.6	15.3	11.1	4.2	31.9	37.5
.	815	80.1	17.5	2.3	27.2	12.9	10.4	31.4	18.0
Kenya									

Table B3: **Sample Composition by Country-Wave**

	N	Percent of responses							
		Firm size (employees)			Sector				
		5 to 19	20 to 99	>100	Manufacturing	Retail	Hospitality	Services	Other
Jul-Sep 2020	789	41.6	37.4	21.0	18.1	13.3	17.7	26.4	24.5
Oct-Dec 2020	658	48.8	30.2	21.0	19.2	12.9	14.8	27.9	25.3
Apr-Jun 2021	802	57.9	30.7	11.5	17.0	12.6	15.8	29.8	24.8
Madagascar									
Jul-Sep 2020	257	38.5	38.1	23.3	11.2	14.1	13.7	46.9	14.1
Jan-Mar 2021	350	50.0	32.9	17.1	12.4	8.3	8.3	52.1	18.9
Malawi									
Oct-Dec 2020	647	68.8	25.0	6.2	11.9	29.7	21.9	29.4	7.1
Mali									
.	216	68.1	25.0	6.9	11.6	20.8	3.2	22.7	41.7
Nigeria									
Jul-Sep 2020	325	47.4	49.8	2.8	17.5	9.5	8.3	30.2	34.5
Senegal									
Apr-Jun 2020	436	55.0	29.6	15.4	31.2	23.9	3.0	21.6	20.4
Jan-Mar 2021	328	64.6	25	10.4	30.8	24.4	2.7	20.1	22.0
Sierra Leone									
Oct-Dec 2020	116	76.7	16.4	6.9	8.6	22.4	13.8	43.1	12.1
Jan-Mar 2021	96	82.3	11.5	6.3	11.5	21.9	20.8	40.6	5.2
South Africa									
Apr-Jun 2020	1035	57.6	37.5	4.9	16.9	10.0	11.0	34.1	27.9
Oct-Dec 2020	242	66.5	30.2	3.3	19.6	8.8	10.0	36.3	25.4
Jul-Sep 2021	270	58.1	35.9	5.9	14.6	6.7	15.0	39.3	24.3
Sudan									
Oct-Dec 2021	49	89.8	10.2	0.0	10.2	40.8	10.2	30.6	8.2
Tanzania									
Jul-Sep 2020	193	51.8	38.9	9.3	40.4	14.5	14.0	21.2	9.8
Oct-Dec 2020	301	83.7	13.6	2.7	33.9	7.0	13.3	11.3	34.6

Table B4: **Sample Sizes in Each Quarter**

	Apr-Jun 2020	Jul-Sep 2020	Oct-Dec 2020	Jan-Mar 2021	Apr-Jun 2021	Jul-Sep 2021	Oct-Dec 2021	Jan-Mar 2022	Full sample
Countries covered	9	11	10	13	6	13	2	1	41
Subjective distributions in the raw data	6,330	6,425	5,313	4,964	4,113	9,769	1,161	616	40,763
Subjective distributions in the clean data	4,460	4,552	4,303	3,818	2,390	6,696	639	188	28,612
Fraction of total									0.70
Well-formed distributions	2,523	2,085	2,774	2,523	2,139	6,352	632	128	20,062
Fraction of total									0.49
Distributions where at least one probability is imputed or rescaled	1,937	2,467	1,529	1,295	251	344	7	60	8,550
Fraction of total									0.21

Notes: The number of countries reported in the Full Sample column only counts a given country once. The sum of observations across quarters does not equal the number of subjective distributions in the full sample because date of the interview is missing in some records. To compute average expected sales and average subjective uncertainty we only use the sample for which we can compute a measure of subjective uncertainty after making modest imputations to the probability vector. That sample excludes distributions where two or more support points are missing or where the subjective uncertainty is zero because the distribution places 100% of the probability mass on a single outcome.

C. Extended Model Allowing for Endogenous Entry and Exit, and Costly External Finance

This section describes extensions to the baseline model in Section 4.

C.1 Setup and incumbent managers' problem with operating leverage

To allow for endogenous entry and exit, we introduce a fixed operating cost that creates operating leverage. Net income (i.e., before considering investment or external financing) equals variable profits less a fixed cost of operation: $Azk^\alpha - f$. Facing that fixed cost, some managers might prefer to liquidate the firm and give up future cash flows instead of continuing to operate at a loss. Versions of the model without entry and exit set $f = 0$.

The managerial investment problem involves to decisions. The first is whether to liquidate the firm or remain in the market for one more period. Conditional on remaining, the second decision involves choosing how much capital the firm will have next period k', subject to depreciation and investment: $k' = i + k(1 - \delta)$.

Because investment is partially irreversible, liquidating the firm or scaling down the capital stock are subject to a resale loss γ. Thus, buying a unit of capital lowers the firm's free cash flows by one unit, but the resale price for that capital upon disinvestment or liquidation yields a proportional loss of $\gamma \in [0, 1]$.

The firm's free cash flows are total profits adjusted for investment activities:

$$\pi(z, k, k') \equiv Azk^\alpha - f - [k' - (1 - \delta)k] \cdot [1 - \gamma \cdot \mathbf{1}(k' < (1 - \delta)k)] \,.$$

If the manager's choices result in negative free cash flows, they bring in outside capital to finance the firm. To allow for costly external financing that can impact investment decisions, we assume external financing incurs a proportional cost $\psi \geq 0$.

We assume our manager-entrepreneurs maximize the net present value of cash flows, discounted at the world interest rate r that they take as given. Incumbent managers' dynamic programming problem is therefore:

$$\begin{aligned}
\tilde{V}(z,k) &= \max\left\{\tilde{V}^l(z,k), \tilde{V}^c(z,k)\right\} \\
&\text{where} \\
\tilde{V}^c(z,k) &= \max_{k'}\left\{\pi(z,k,k') \cdot [1 + \psi \cdot \mathbf{1}(\pi(z,k,k') < 0)] + \frac{1}{1+r}\widetilde{\mathbf{E}}[\tilde{V}(z',k')]\right\} \\
\tilde{V}^l(z,k) &= Azk^\alpha - f + k(1-\gamma).
\end{aligned}$$

In words, a manager's valuation of their firm $\tilde{V}(z, k)$ is the highest between the liquidation

value $\tilde{V}^l(z,k)$ and the value of continuing to operate $\tilde{V}^c(z,k)$. The liquidation value is current net income plus the resale value of invested capital. When the manager chooses to continue operating, they choose capital next period k' to maximize the sum of current cash flows (inclusive of external financing costs) and the discounted expected value of the firm one period ahead $\widetilde{\mathbf{E}}[\tilde{V}(z',k')]$. The operator $\widetilde{\mathbf{E}}[\cdot]$ takes expectations under the manager's *subjective* stochastic process for future profitability z' from equation 6 in the main text.

C.2 Potential entrants' investment and entry options

In the extended model with endogenous entry and exit, there is a fixed mass M of potential entrepreneurs who observe a signal of their firm's initial profitability z_0 drawn from the unconditional distribution of the objective process in equation 5, so $z_0 \sim \mathcal{N}(0, \sigma^2/(1-\rho^2))$. Potential entrants then face two choices. They must decide whether to enter the market, and, if so, how much initial capital k_1 to inject into the business. That initial capital costs the manager $(1+\psi^e)$ times the amount invested, so ψ^e represents initial financing and startup costs.

Potential entrants' problem is therefore:

$$\tilde{V}^e(z_0) \;=\; \max\left\{0, \max_{k_1}\left[-k_1\cdot(1+\psi^e) + \frac{1}{1+r}\widetilde{\mathbf{E}}[\tilde{V}(z_1,k_1)]\right]\right\},$$

where again the manager forecasts $z_1|z_0$ using the subjective stochastic process from equation 6 in the text.

C.3 Stationary equilibrium

A stationary equilibrium in the extended model with entry and exit is characterized by manager valuations of their incumbent and entrant businesses $\tilde{V}(z,k)$ and $\tilde{V}^e(z_0)$, a wage w, and a stationary distribution of firms $\phi(z,k)$ such that:

- $\tilde{V}(z,k)$ solves the incumbent manager's problem;
- $\tilde{V}^e(z_0)$ solves the entrant's problem;
- The stationary distribution of firms across the state space $\phi(z,k)$ is consistent with incumbent firms' investment policy $k^*(\cdot)$ contingent on not liquidating, entrants' policy $k^e(\cdot)$ contingent on entering, and the *objective* law of motion of profitability

$Pr(z'|z)$ from equation 5 in the main text:

$$\phi(z',k') = \begin{bmatrix} \int_{z,k} Pr(z'|z) \cdot \mathbf{1}(k^*(z,k) = k') \cdot \mathbf{1}(\tilde{V}^l(z,k) < \tilde{V}^c(z,k)) \cdot \phi(z,k)\mathrm{d}z\mathrm{d}k \\ +M \int_{z_0} Pr(z'|z_0) \cdot \mathbf{1}(k^e(z_0) = k') \cdot \mathbf{1}(\tilde{V}^e(z_0) > 0) \cdot \phi_0(z_0)\mathrm{d}z_0 \end{bmatrix};$$

- The labor market clears, so $\int_{z,k} n^*(z,k;w)\phi(z,k)\mathrm{d}z\mathrm{d}k = 1$.
- The mass of entrants M equalizes entry and exit:
  $\int_{z,k} \mathbf{1}(\tilde{V}^l(z,k) \geq \tilde{V}^c(z,k)) \cdot \phi(z,k)\mathrm{d}z\mathrm{d}k = M \int_{z_0} \mathbf{1}(\tilde{V}^e(z_0) > 0) \cdot \phi_0(z_0)\mathrm{d}z_0$.

Aggregate value added (the analog to GDP in the data) in equilibrium is the sum of output less the fixed cost of operation across all firms in the economy. After choosing its optimal labor, a firm's output is proportional to variable profits:

$$\hat{A}\hat{z}k^{\tilde{\alpha}\nu}(n^*)^{(1-\tilde{\alpha})\nu} = Azk^{\alpha}\frac{[(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu}}{(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu}.$$

Therefore, aggregate value added is:

$$Y = \int_{z,k} \left[\frac{[(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu}}{(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu} Azk^{\alpha} - f \right] \cdot \phi(z,k)\mathrm{d}z\mathrm{d}k.$$

C.4 Calibration with entry and exit

When we consider versions of the model with entry and exit, we impose a target exit rate of 5% per half-year in each economy, consistent with long-run estimates for the US and other high and middle-income countries (see, e.g., Crane et al., 2022, Hsieh and Klenow, 2014, and Kochen, 2022). To a first order, the fixed cost of operation f governs the entry/exit rate, as higher values of f erode free cash flows and incentivize liquidation conditional on the other parameters, especially TFP A, capital irreversibility γ and volatility σ.

C.5 Calibration with costly external financing

In our baseline specifications, allow incumbents to finance investments with external funds frictionlessly ($\psi = 0$). Our data and model do not speak directly to financing frictions, so we avoid introducing parameters into the model that we cannot discipline empirically.

However, a reasonable assumption for small and medium businesses in emerging and developing economies could be that they need to finance all day-to-day investments with internal funds. Thus, our robustness exercises in Table 8 impose $\psi = \infty$, which also limits incumbent managers' ability to invest solely out of a signal of high profitability. The table

does not consider a specification with endogenous entry and exit as well as costlyfinancing, but we think a 5% cost on entrants' initial capital injection ($\psi^e = 0.05$) could be a reasonable assumption for that case.

C.6 Adjusting for Jensen's inequality effects

Our log-Normality assumption about profitability z leads to a situation where high uncertainty $\tilde{\sigma}$ volatility σ can raise managers' propensity to invest by raising raising the average perception and realization of z, through Jensen's inequality effects. The specification in the second row of Table 8 adjusts for this issue by multiplying variable profits by $\exp[-\tilde{\sigma}^2/2]$ and adjusting TFP residuals upward by $\exp \sigma^2/[2(1-\rho^2)]$. We opt not to adjust for these Jensen's effects in our baseline specification because we think they are more of a feature than a bug of our framework. They imply more fat-tailed firm-size distributions in developing countries, consistent with dominance of a few large firms and with evidence of greater log-productivity dispersion as documented by Ayerst et al. (2024).

Our specification that abstracts from investment frictions, setting $\gamma = 0$ in row 6 of Table 8 similarly adjusts the variable profit function by a factor of $\exp[\sigma^2 - \tilde{\sigma}^2/2]$. The reason is that without frictions, managers set the user cost of capita $\delta + r$ equal to its expected marginal benefit $\tilde{\mathbf{E}}[Azk'^{\alpha-1}]$. Thus, a discrepancy between $\tilde{\sigma}$ and σ distorts managerial investment through a first-moment Jensen's effect directly, and we would rather our model not capture such an effect.