Business Uncertainty in Developing and Emerging Economies[*]

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Abstract

We study business uncertainty in high- versus low-volatility environments by surveying over 31,000 managers across 41 countries. We elicit subjective probability distributions for future own-firm sales and measure firm-level uncertainty with their mean absolute deviations. Analogously, we measure realized volatility using absolute forecast errors. We establish two new facts. (1) Subjective uncertainty and realized volatility both decline with GDP per capita. (2) Managers underestimate volatility everywhere (they are *overprecise*), but more so in low-volatility rich countries. We build a heterogeneous-firm dynamic model and show that our facts imply larger TFP gaps between the US and developing/emerging economies. In the model, high volatility generates investment and growth opportunities in poor countries. But high uncertainty and low overprecision slow reallocation and pull down poor-country output. Quantitatively, the volatility effect dominates, so we infer 30 to 40% lower TFP in poor countries to reconcile their high volatility and low GDP per capita.

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

Keywords: Managers, uncertainty, volatility, aggregate TFP, real options, development accounting

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1. Introduction

How do business managers perceive uncertainty in high-volatility environments? How do uncertainty and volatility—i.e., perceived and actual risk—shape investment, reallocation, and productivity? These are fundamental and yet challenging questions for corporate finance and macroeconomics. Subjective uncertainty, as perceived by managers over future firm outcomes, is not easily observable. Common proxies based on realized or implied volatility of stock returns or sales growth differ systematically from survey-based measures (e.g., see Ben-David et al., 2013; Boutros et al., 2020; Barrero, 2022). And when subjective measures of uncertainty are available at the firm level, it is often in stable, advanced economies in the mid-2010s and later (e.g., Altig et al., 2022; Kumar et al., 2023; Bachmann et al., 2024). Thus, it is hard to study uncertainty, volatility and their implications for investment across systematically different environments.

We address these challenges by surveying over 31,000 managers across 41 countries, measuring subjective uncertainty and realized volatility (i.e., absolute forecast errors) over future own-firm sales. Aggregating those measures by country and country-sector, we establish new facts about uncertainty and volatility in high- and low-risk environments. We examine the implications by building a dynamic model in which manager perceptions of uncertainty and realized sales volatility both matter for outcomes. Then we quantify the model to match our facts, and trace the implications for investment, reallocation, and aggregate TFP in high- versus low-volatility 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 subjective distributions have three support points; namely, a central, an optimistic, and a pessimistic scenario. We obtain managerial forecasts or expectations from the first moment of each distribution, and measure subjective uncertainty using its mean absolute deviation. In a subset of countries we also track firm outcomes across time and construct absolute forecast errors to measure realized volatility. Our work focuses on sales projections because they are central to managerial planning, as noted by Graham (2022).

We validate our data by replicating key results from prior work on managerial forecasts and uncertainty, including Bloom et al. (2021) and Bachmann et al. (2024). Managers who expect higher future sales later report higher actual sales. Those who report more uncertainty go on to make larger absolute forecast errors. They report high uncertainty in volatile situations; for example, after seeing large (positive or negative) shifts in sales.

Hiring decisions and plans also line up with expectations and uncertainty, consistent with experimental evidence developed 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 business-cycle indicators in each country. In Figure 1 and elsewhere in the paper 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.

Our data don't establish causal links between uncertainty, volatility and GDP per capita. They do show that firm-level sales are systematically more difficult to forecast in poor countries, and that managers recognize it. Our results are consistent with prior work, such as by Haltiwanger et al. (2008) and Asker et al. (2014), that estimates greater variability in firm employment and productivity in poor countries. It is also consistent with work on macro volatility. For example, Koren and Tenreyro (2007) show how country-specific macro shocks are more volatile in the developing world. We go further than this prior work by establishing that variability from managers' viewpoints and information sets; that is, we show it reflects *unforecastable* variation that raises managerial uncertainty.

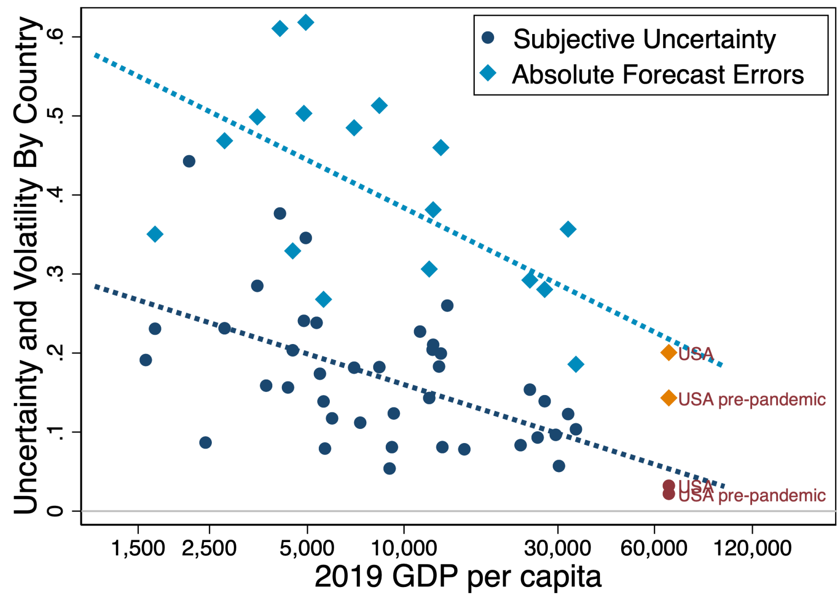
Although managers perceive high uncertainty in volatile environments, they systematically underestimate volatility; namely, they are *overprecise*.[1] Figure 1b plots average absolute forecast errors (i.e., realized volatility) by country against subjective uncertainty. If managers had rational expectations 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 forecast errors exceeding uncertainty in 85 out of 89 individual country-sectors. We develop a new method to test whether common shocks explain away these patterns, and conclude they do not. Instead, managers seem to systematically underestimate firm-specific sales risk.

In percentage terms, however, overprecision seems to be more severe in rich countries.

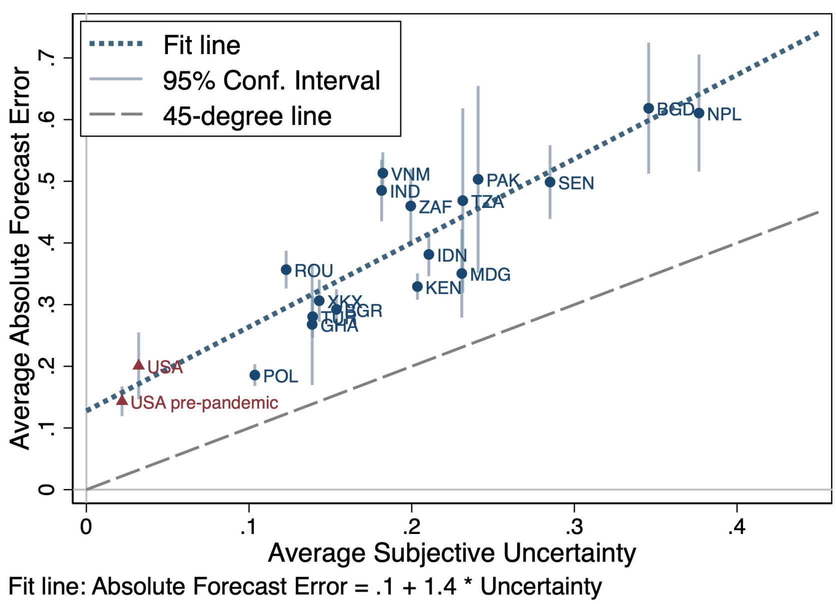
[1]Other authors refers to this phenomenon as *overconfidence* because it is equivalent to the manager overestimating their ability to make accurate forecasts, or *miscalibration* to emphasize the discrepancy between the subjective stochastic process that managers use and the econometrician's. We prefer 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**



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.

That means managers in the rich world tune out a larger share of the risk in future sales. We can see this result in Figures 1a and 1b, which 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. This result adds to time-series and rich-country evidence on overprecision. For example, Boutros et al. (2020) find US managers are persistently overprecise, and Lochstoer and Muir (2022) show that investors underreact to market volatility spikes on impact. We contribute new evidence of overprecision among managers in dozens of countries and show that its severity rises with development.

Having documented new facts about uncertainty and volatility across countries, the second major contribution of our paper is to quantify their implications. To do so, we build a heterogeneous-firm dynamic model featuring convex demand for capital and real investment options. We follow Barrero (2022) in assuming that managers use a subjective stochastic process to forecast firm profitability, and let its conditional volatility differ from that of the objective profitability process. Investment decisions, thus, depend separately on subjective uncertainty and realized volatility, which we can match to the data.

To find out how much uncertainty and volatility matter for investment and reallocation, we run development accounting exercises (see, e.g., Caselli, 2005; Hsieh and Klenow, 2010) that weigh up our empirical evidence against well-known productivity and income gaps across countries. We assume firms operate under the same investment frictions and technology everywhere, up to a country-specific TFP shifter. Then we ask, how low does that TFP shifter need to be to account for (1) a country's relative GDP per capita and (2) our cross-country facts about uncertainty and volatility? Concretely, what do we infer about a poor country's TFP when we know its firms' sales are highly volatile, and its managers underestimate that volatility modestly?

When poor-country firms are subject to high volatility, we need *lower* TFP to justify those countries' low GDP per capita. The reason is firm value and investment are convex functions of profitability, a canonical feature of the class of models we consider. Under high volatility, that convexity translates into high chances of becoming highly profitable, accumulating capital, and growing via a classic Oi-Hartman-Abel effect (Oi, 1961; Hartman, 1972; Abel, 1983). Reconciling poor countries' high volatility and low GDP per capita requires *lower* TFP to explain why their managers don't invest in the growth opportunities brought by high volatility.

Modest overprecision in poor countries pushes against this volatility effect. Overprecise managers underestimate sales risk and and therefore undervalue the real options that let them delay investment decisions. (See, e.g., Abel and Eberly, 1996; Abel et al., 1996; Guiso and Parigi, 1999; Bloom et al., 2007; Bachmann and Bayer, 2013; Baker et al., 2024.) They liquidate the firm quickly when profitability drops, and they invest and disinvest readily in response to shocks. In poor countries, modest overprecision dampens these dynamics, slowing reallocation and lowering GDP per capita; that is, relative to rich countries with high overprecision and swift reallocation. Because these differences in overprecision help explain why poor countries lag behind, they imply *higher* TFP in those poor countries.

We quantify the model to match our facts and assess the relative strength of the volatility (Oi-Hartman-Abel) and overprecision effects, which push in opposite directions. We consider eight versions of the model and always find the volatility effect dominates. Thus, our facts imply larger TFP gaps between the US and developing/emerging economies. In our preferred specifications, we infer 30 to 40% lower TFP in countries with $5,000 GDP per capita (similar to Kenya), compared to a counterfactual world where all countries have the same low volatility and no overprecision. Even in the most conservative version of the model, our facts imply 15% lower TFP in such countries.

Our results challenge the view that persistently high cash flow volatility is, on its own, a strong deterrent to investment in the developing world. Low TFP in stands in for unmodeled forces that restrain managers from investing in response to good shocks. Inferring lower TFP in poor countries when we acknowledge their managers' high uncertainty and volatility means that those forces must be stronger in a world where our facts hold. We are, however, limited in our ability to identify specific forces. Finance is surely part of the story. High costs of capital due to risk premiums or impatience (e.g., see David et al., 2014 and Falk et al., 2018) could restrain investment in developing countries. So could reallocation frictions of the sort that Eisfeldt and Rampini (2006) find to be countercyclical in advanced economies. Financing constraints could deter poor-country managers from investing in their firms' productivity, especially when combined with high volatility, as Vereshchagina (2022) suggests. But non-financial forces can also restrain investment. If sales shocks are volatile yet transitory in poor countries, there is little reason to respond to them. Scaling up when opportunities arrive might be hard for poor-country managers, as Akcigit et al. (2021) suggest. Our data and model can't link specific fundamentals to high volatility and low GDP per capita. But they do say that high uncertainty and volatility in poor countries must come alongside other forces that restrain investment and depress TFP.

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 learn more about about the surveys from Apedo-Amah et al. (2020).

Our dataset covers 41 countries from all of the regions covered by the World Bank and a range of development stages.[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 respondents from the first wave, letting us track those firms' performance over time. In the remaining 23 countries we only have data from a single wave (i.e., a single cross-section). Altogether, our dataset includes 67 country-wave combinations. 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.

Firms in our dataset come from most 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 in coverage across countries, and because governments often play a large role in those

[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 that fielded the broader survey.

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). We focus on sales 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, we ask managers for a central scenario for the firm's sales looking six months ahead (expressed as a percentage change from the same period in the prior year) and a probability for that outcome. Then we ask them to consider a more optimistic and a more pessimistic scenario, asking for a sales outcome and probability for each. 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:

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

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

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

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.

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 have such data from 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 sales level in the 30 days prior, expressed relative to the same reference period as in the original interview.[5] We treat sales outcomes in those follow-up waves as the realizations corresponding to the forecasts from the first wave and use them to construct forecast errors.

We interpret average absolute forecast errors within a country or country-sector as measures of realized sales volatility. Those averages capture the magnitude of realized shocks that managers cannot forecast, in the same spirit as the indices developed by Jurado et al. (2015). Throughout the paper we refer to average absolute forecast errors and (realized) 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. We cannot compute our expectations and uncertainty measures for all those responses, unfortunately. To do so we need: (1) the probability distribution to have at least two separate support points for potential future sales; (2) the sum of the probabilities to equal 100; and (3) at least two support points to have positive probability mass.[6] In some cases we make minor imputations to the probability vector provided by a respondent to obtain a distribution that yields measures of expectations and uncertainty. 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.

Our analysis dataset, after all cleaning and imputation procedures, includes 28,612 subjective distribution observations from 41 countries. That is 70% as many in the raw sample of 40,763. Among them, 8,550 (30% of the final sample) have a rescaled or imputed the 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. We view our data collection effort as successful, at least in comparison with work by Bloom et al. (2021), who obtain subjective distributions from 85% of US

[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.7 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.

manufacturing plants responding to a mandatory Census survey. Our data collection efforts contribute to a growing literature on business expectations surveys reviewed by Born, Enders, Müller, and Niemann (2023).[7] We stand out for providing business expectations and uncertainty data from a cross-section of dozens of developing and emerging economies.

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**
	Pessimistic	-0.45	0.56	0.48
Support point for future sales	Central	-0.08	0.42	0.37
	Optimistic	0.16	0.30	0.27
	Pessimistic	27.3	16.1	15.2
Probability	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
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.

2.3 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

[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.

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 around those averages, 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 absolute forecast errors. It also reveals vast cross-firm heterogeneity in expectations and uncertainty across firms. 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. We use employment weights here and in most of our empirical work to provide estimates that reflect aggregate activity. That said, our key results are not sensitive to weighting.[8]

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).

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 similar findings in Altig et al. (2022), Barrero (2022), and Bloom et al. (2021). It also validates our measures of managerial expectations as forecasts of subsequent sales.

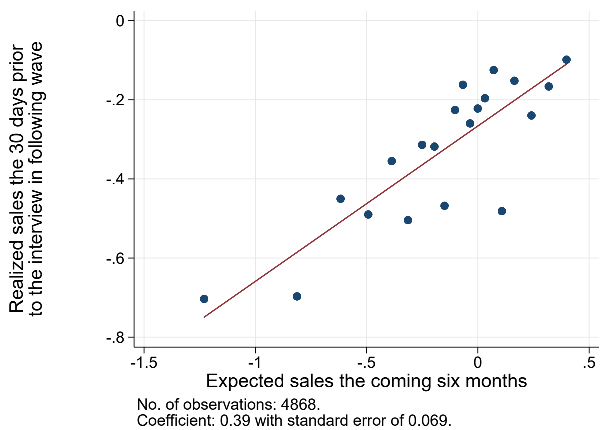
We also find a positive relationship between subjective uncertainty and absolute forecast errors, shown in panel (b) of Figure 2. Managers who express higher uncertainty

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

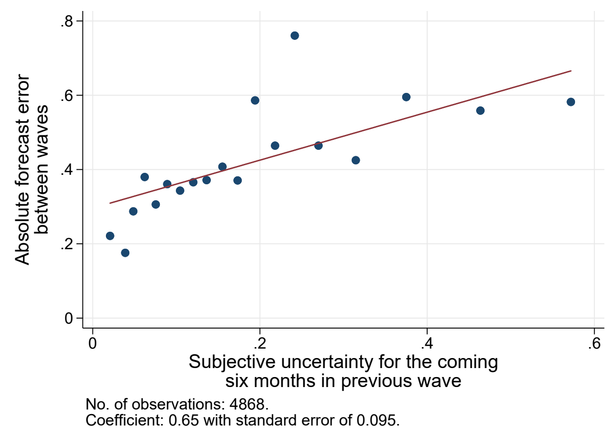
ex-ante make forecasts that are less accurate ex-post. This is the same relationship uncovered by Altig et al. (2022) and Barrero (2022). It suggests that managers express higher uncertainty when they foresee their firm being subject to higher volatility; that is, larger sales shocks.

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

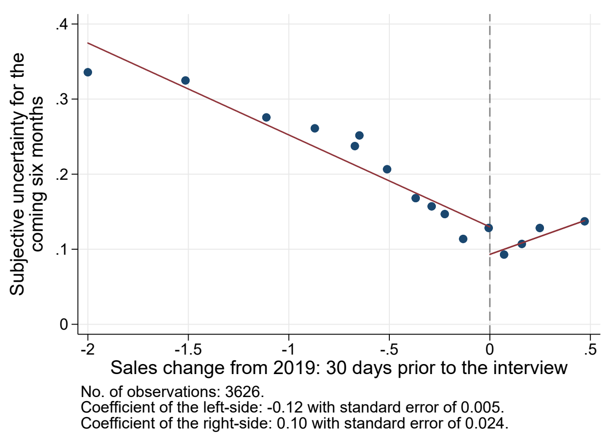
(a) **Expectations Predict Future Sales**



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



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



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.

Table 3: **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. $^{+}$ $p < 0.15$ * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 3. Thus, our measures of expectations and uncertainty are consistent with managers' current or planned actions. Columns 1 to 3 of Table 3 regress changes in employment in the 30 days prior to the interview on expectations and uncertainty about six-months-ahead sales. Managers who forecast rising sales report higher recent employment growth. Those who report high uncertainty tend to report lower employment growth. Columns 4 to 6 use expected employment changes as the dependent variable. Initial waves of the BPS had a module that elicited subjective probability distributions for future employment, similar to those about future sales in Table 1. We compute expected changes in employment and show they correlate with our measure of sales expectations. Columns 7 and 8 also link uncertainty about future sales to uncertainty about future employment. When managers anticipate the possibility of large shifts in sales, they also anticipate a wide range of shifts to employment.

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

We establish two new facts about cross-country business uncertainty and 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; namely, 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, 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 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).[9] 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 computed 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 which yield measures of uncertainty and absolute forecast errors comparable to 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 4 and 5 use firm-level microdata regressions to show that managers in poor countries are systematically more uncertain and make systematically larger forecast errors than their peers in rich countries. We regress firm-level uncertainty or absolute forecast errors, respectively, on a range of micro and macro characteristics. We include those controls to show the headline relationships with GDP per capita are not easily explained by sampling differences across countries, or swamped by within-country heterogeneity in uncertainty and volatility. For example, if 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) that could explain why uncertainty and volatility decline with GDP per capita.

[9]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.

Table 4: **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 5: **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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) of Tables 4 and 5 dispels those concerns by controlling for first-order differences in our samples across countries. The controls include 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 4 and -0.11 for absolute forecast errors in Table 5. 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? Column 2 of Tables 4 and 5 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 4. Similarly, we add uncertainty at the time of forecast as a predictor of future absolute forecast errors in Table 5, as suggested by Figure 2b. Capturing cross-firm heterogeneity in this way results in only a modest reduction of the GDP per capita coefficient. The estimates look similar as we consider additional 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 include 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 inconsistent with our broad finding that business uncertainty and volatility decline with development.[10]

Appendix Tables A.3 to A.8 repeat the regression analysis from Tables 4 and 5 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.3 and A.6 run the analysis on the manufacturing sector only. Tables A.4 and A.7 focus on medium-sized firms with 20 to 99 employees. Finally, Tables A.5 and A.8 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

[10]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

responses from managers who do not provide a distribution with three support points and probabilities that add to 100.[11] After adding macro controls, the coefficient on GDP declines modestly but remains statistically significant in all but one of those tables.

We find little evidence, by contrast, that business expectations vary systematically with economic development. Table A.2 in the appendix follows the same format as Tables 4 and 5 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 and realized sales volatility decline with GDP per capita echoes prior work by Koren and Tenreyro (2007), who show that country-specific aggregate shocks are more volatile in poor countries than in rich ones. It is also 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). Our main contribution relative to that work is 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 lower-quality data, 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 evidence does 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.1 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

[11]Imputing the probability vector doesn't matter very much because the support points of the distribution matter much more for expectations and uncertainty, as Altig et al. (2022) show.

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 ponder their implications, while remaining agnostic about the underlying mechanisms.

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).

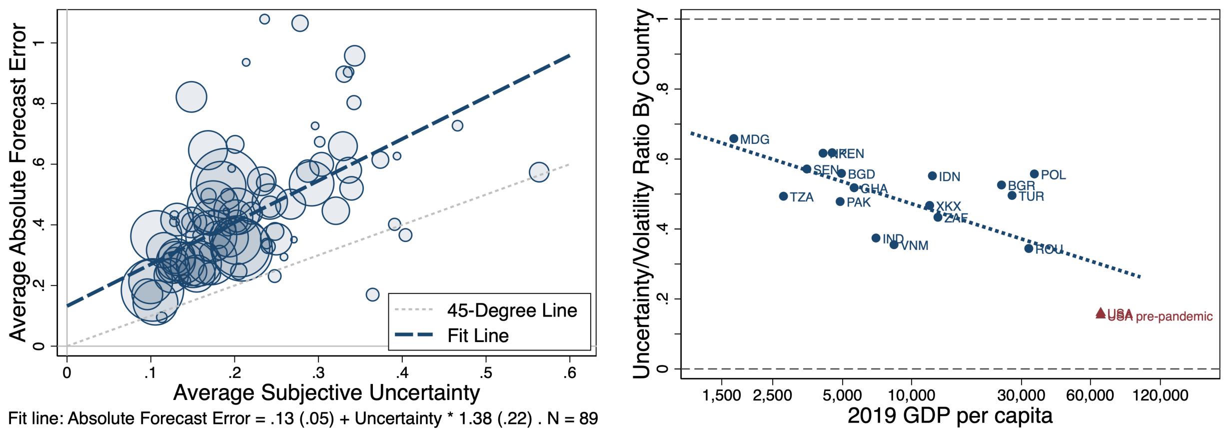
Figure 1b shows that measured volatility (i.e., average absolute forecast errors) exceeds uncertainty with 95% confidence in every country where we can measure both. The pattern extends to US data from the Atlanta Fed's Survey of Business Uncertainty. Recall from equations 2 and 3 that our measures of uncertainty and volatility are analogous, but uncertainty comes from managers' (ex-ante) subjective distribution and volatility reflects (ex-post) sales shocks. Thus, 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, with the plot tracing the 45-degree line. The pattern in Figure 1b instead suggests that managers systematically underestimate own-firm sales risk.

We find the same pattern when we measure average uncertainty and volatility for 89 country-sector combinations in the World Bank data and plot them in Figure 3a. The size of each marker is proportional to the number of forecast-error observations in that country-sector. We weight our estimates by those sample sizes to avoid drawing inferences from country-sectors with few observations. Figure 3a shows 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. That means managerial uncertainty also underestimates volatility in our country-sector dataset. Indeed, average absolute forecast errors exceed subjective uncertainty in 85 of 89 country-sector observations. The few cases where it does not are smaller bubbles, where we should expect noisier averages.

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 of 1.3 and 1.4. 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*. Figure 3b corroborates that conclusion by plotting the ratio between

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 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.

average uncertainty and average volatility (absolute forecast errors) by country against GDP per capita, revealing a downward sloping relationship with all data points below 1. (Rational expectations and the absence of large common shocks would imply uncertainty-to-volatility ratios near 1.) Among poor countries whose 2019 PPP GDP per capita is 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. This result says that rich-country managers are much less attuned to uncertainty than their counterparts in developing/emerging economies. Rich-country firms are not just subject to smaller shocks; their managers perceive disproportionately less uncertainty as GDP per capita rises and volatility falls.

That managers are more overprecise in rich countries raises questions about the nature of 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 imply that the pool of potential business leaders in rich countries is small and skewed towards those who have good ideas and underestimate risk. Alternatively, firms in rich countries might be better at selecting leaders who are resolute and take action swiftly, which may suit shareholders and implicitly select overprecise managers (see, e.g., Bolton et al., 2013). If rich-country firms have more demand for these traits, that could explain why the typical CEO especially overprecise in those countries.

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 easily inflate absolute forecast errors without also raising subjective uncertainty. If managers systematically underestimated macro volatility in this way, that would be consistent with our thesis that they underestimate their firms' sales risk. But in our setting with one to two cross-sections of forecast errors by country, large common shocks are a greater concern. 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. Such shocks could inflate our volatility measures even if managers are not overprecise.

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). The two terms on the right-hand-side are the square of the average forecast error (i.e., the bias or common shock) and the variance of forecast errors in the country.

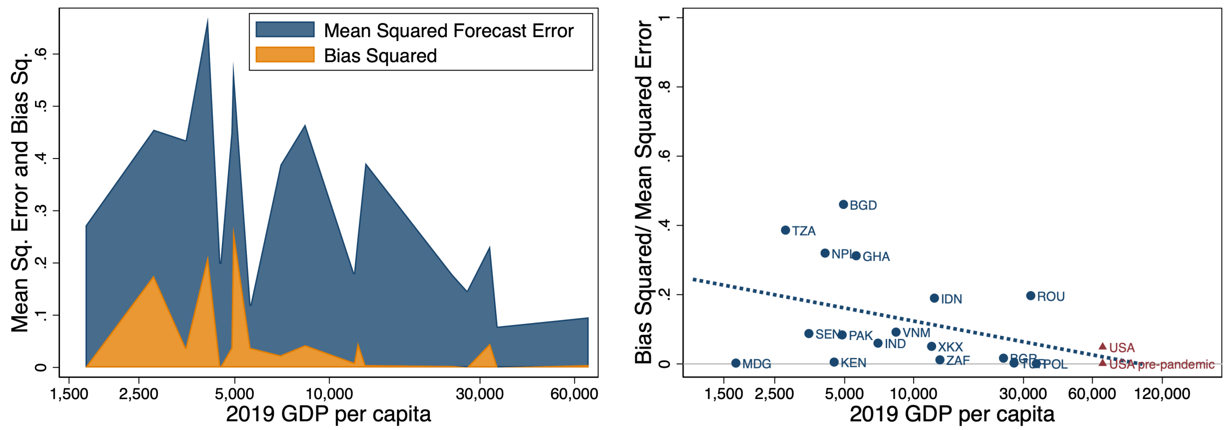
Figure 4a plots the total mean squared error (MSE) and the bias squared component in our main cross-country sample. It reveals a modest contribution of the bias squared term throughout, implying that common shocks are not the primary driver of measured volatility. Figure 4b corroborates this observation by plotting the ratio between bias 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 about 20% of mean squared forecast errors in countries with less than $5,000 in GDP per capita.

We corroborate that our estimates of overprecision are robust to dropping countries or

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.

country-sectors with large bias components in Table A.9 in the appendix. We estimates an average difference between absolute forecast errors and uncertainty of about 0.2 and an average ratio of about 0.5 between them. The ratio barely changes when we drop countries or country-sectors with larger bias components.[12]

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 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*. In the process we discover that common (macro) shocks seem to be larger, but still modest, contributors to forecast errors in low-

[12]Figure A.5 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.

income countries, consistent with Koren and Tenreyro (2007). Below, we design our model and quantitative analyses to accommodate these data patterns in addition to the earlier evidence on overprecision.

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 how (and how much) those differences matter, we build a dynamic model in which managerial decisions depend on ex-ante uncertainty as well as realized volatility.

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 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

There is a unit mass of entrepreneurs who manage their own business by investing in capital k and hiring labor n locally. Businesses produce output $\hat{y}$ 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 static variable profits, taking the equilibrium wage w as given. After optimizing, variable profits are proportional to output, and we can write them down as a function of capital and two idiosyncratic and aggregate TFP shifters z and A that are simple transformations of their counterparts in equation 4:[13]

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

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.[14]

[13] 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 $z \equiv \hat{z}^{\frac{1}{1-(1-\hat{\alpha})\nu}}$.

[14] 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.

Net income (i.e., before considering investment or external financing) equals variable profits less a fixed cost of operation: $Azk^{\alpha} - f$. This fixed cost generates operating leverage that leads some some managers to liquidate the firm and give up future cash flows, instead of continuing to operate at a loss.

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:

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

Managers are overprecise (they underestimate the conditional volatility) if and only if $\tilde{\sigma} < \sigma$. While this specification for the beliefs process is a reduced form, it is possible to derive it 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 Incumbent managers' investment and liquidation options

Incumbent managers observe their firm's current profitability z and capital k, and make two choices. The first concerns whether to liquidate the firm or remain in the market for one more period. Conditional on remaining, they choose how much capital the firm will have next period k'. The law of motion for capital takes into account depreciation and investment, so that $k' = i + k(1 - \delta)$.

Investment and liquidation are subject to adjustment costs. We focus on the case with partially irreversible investment. Buying a unit of capital lowers the firm's free cash flows by one unit, but the sale price for that capital at the time of disinvestment or liquidation yields a proportional loss of $\gamma \in [0, 1]$. This resale loss captures any firm-specificity of investment, for example. The model can support other forms of adjustment costs. We focus on partial irreversibility because γ has a clear economic interpretation and we are interested in how uncertainty changes managers' valuation of real investment and liquidation options. If, instead, we wanted to match investment dynamics closely, we might use quadratic adjustment costs and estimate them using panel data.

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 and incur a proportional cost ψ. External financing is therefore costly and is another friction to investment when $\psi > 0$.

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. Making profitability and, implicitly, sales projections central to investment decisions is consistent with actual capital budgeting practices reviewed by Graham (2022).

4.4 Potential entrants' investment and entry options

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 also 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 injection costs the manager $(1+\psi^e)$ times the amount invested, so ψ^e represents initial financing and startup costs.

Potential entrants' problem is therefore:

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

where again the manager forecasts z_1 using the subjective stochastic process from 6 conditional on z_0.

4.5 Stationary equilibrium

A stationary equilibrium is characterized by manager valuations of 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 law of motion of profitability $Pr(z'|z)$:

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

- 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:

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

4.6 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 variables using 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 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.

4.7 Small sample bias in sales forecasts

We introduce an i.i.d., country-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 6 and 5). We introduce this common shock to output to help our model match a key feature of our data which we document 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. Our measure of realized volatility, based on average absolute forecast errors, therefore depends on the common shock $\mathcal{A}'$ and the objective conditional volatility σ of z'.

5. Development accounting with cross-country differences in uncertainty and volatility

We use a series of development accounting exercises in the spirit of Caselli (2005), and Hsieh and Klenow (2010) to study how our facts about cross-country uncertainty and volatility matter for investment, reallocation, and productivity. Our goal is to ask:

- How much do manager perceptions of uncertainty in high- and low-volatility environments change the incentives to invest and reallocate capital across firms?
- How much do differences in realized volatility affect investment and reallocation?

Motivated by the cross-country facts from Section 3, we frame our analysis in terms GDP per capita gaps. Poor countries are characterized by high volatility and low overprecision when compared to rich ones. What does this combination imply for investment and reallocation in the model from Section 4? Can high uncertainty and volatility (with low overprecision) account for poor countries' relatively low GDP per capita?

5.1 Setup and target moments

Our accounting exercises consider four hypothetical countries defined by their relative GDP per capita levels. The first is a 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 in the US and comparable to Brazil. The fourth's GDP per capita is $5,000, about 8% as high as the US and similar to Kenya. We calibrate our model separately for each country to 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 6 shows our target moments for each hypothetical country. They are employment-weighted average subjective uncertainty and absolute forecast errors; the ratio of squared forecast bias to mean squared forecast error; and a common exit rate of 0.05 to discipline entrepreneurial dynamics and reallocation. We use linear regressions of uncertainty, absolute forecast errors, and the ratio of bias squared to mean squared forecast errors against GDP per capita to obtain the values of those moments. Specifically, we take the regression lines shown in Figures 1a and 4b and we evaluate them at log(66,000), log(33,000), log(15,000) and log(5,000) to obtain the targets for each country. We specifically do not use data points from individual countries in the survey data to focus on the

Table 6: **Full Accounting Exercise: Targets and Relevant Parameters**

Comparable Country	Relative GDP/person	Uncertainty	Abs. Forecast Errors	Bias^2/ MSE	Exit Rate
US	1.00	0.05	0.22	0.02	0.05
Poland	0.50	0.09	0.28	0.06	0.05
Brazil	0.23	0.14	0.35	0.10	0.05
Kenya	0.08	0.20	0.44	0.16	0.05
Key Parameter	A TFP	$\tilde{\sigma}$ Subj. SD	σ Obj. SD	$\mathcal{A}'$ Comm. Shock	f Fixed cost

Notes: This table shows the moments that we target in our development accounting exercise. 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 target an exit rate of 5% per period, equivalent to 10% per year based on the long-run average for the US, Mexico, and several European Countries (e.g., Kochen, 2023). Note that GDP and GDP per Capita are equal in our model economies because we normalize aggregate labor supply across countries. See Section 4.

predictable variation with GDP per capita and drown out any noise from the survey data. Our target exit rate of 5% per half-year is 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).

We fix several parameters governing the technology, shock persistence, and investment frictions across countries. Table 7 shows those parameters and their values in our baseline calibration. We set decreasing returns to capital in the variable profit function, α, based on a capital share of 0.35 in physical output and revenue returns-to-scale of 0.80 (consistent with with 25% markups). The autocorrelation of profitability shocks $\log(z)$ yields a quarterly rate of 0.95 as in Khan and Thomas (2008). The degree of investment irreversibility, with resale losses of 30%, is slightly lower than corresponding estimates in Bloom (2009). In our baseline specification we don't allow incumbents to finance investments with external funds ($\psi = \infty$), a reasonable approximation for small and medium businesses in emerging and developing economies. This assumption also limits incumbent managers' ability to invest solely out of a signal of high profitability. We impose a 5% cost on entrants' initial capital injection ($\psi^e = 0.05$). Our baseline calibration imposes "maximal" frictions on investment. We relax those frictions in Section 5.3 to show our quantitative results don't rely on them.

Our exercises find a vector of parameters, shown in the bottom row of Table 6, that match the target moments for each hypothetical country. Given a vector $\{A, \sigma, \tilde{\sigma}, \mathcal{A}', f\}$, we can obtain model-implied versions of each target moment.[15] Then we search for a vector

[15]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

Table 7: **Accounting Exercise: Fixed Parameters**

Parameter	Description	Value	Notes
$\hat{\alpha}$	Capital share, output	0.35	Conventional
ν	Decreasing returns, output	0.80	20% markups
α	Decreasing returns, var. profit	0.58	$\hat{\alpha}\nu/(1-(1-\hat{\alpha})\nu)$
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
ψ	Cost of external fin., incumbent	∞	No external financing, incumbents
ψ^e	Cost of initial capital, entrant	0.05	cf. Hennessy and Whited (2005)
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 accounting exercises that fit relative GDP per capita, uncertainty, absolute forecast errors, and the exit rate by country. One model period is equivalent to a half-year.

of those five parameters that minimizes the sum of squared distances between the model-implied and data moments. We run this minimization using an identity weighting matrix because this is an exactly-identified minimization where we can fit the data moments very closely (up to the third decimal point in most cases).

There is an intuitive mapping between parameters and moments, so we associate each of the key parameters to a column of Table 6. 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 shocks that managers can't forecast, and therefore the average absolute forecast error;
- the common shock to output $\mathcal{A}'$ introduces an average bias that raises average absolute forecast errors and the ratio of bias squared to mean squared forecast errors;
- the fixed cost of operation f governs the entry/exit rate, as higher values of f erode free cash flows and incentivize liquidation.

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.

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

By fixing the parameters in Table 7 across countries, we make $\{A, \sigma, \tilde{\sigma}, \mathcal{A}', f\}$ do all the work of explaining cross-country differences in uncertainty, volatility, and GDP per capita. Thus, we run a standard calibration that is also a development accounting exercise because we ultimately match GDP per capita gaps. Below, we interpret the country-specific TFP shifters as residual, reduced form parameters that match GDP per capita gaps conditional on all other parameters and moments.

5.2 Uncertainty, volatility, and aggregate TFP

We want to know what our facts about uncertainty and volatility documented in Section 3imply for cross-country TFP gaps. If uncertainty and volatility matter for investment, reallocation, and productivity, matching our facts will require larger or smaller TFP gaps across countries to fit the GDP per capita gaps from the data.

We proceed by running three versions of our accounting exercise. The first matches GDP per capita gaps while ignoring our facts from Section 3. We assume all countries have the same volatility and bias squared to mean squared forecast error ratio as the richest, and we abstract from overprecision. That means $\tilde{\sigma} = \sigma = 0.28$ and $\mathcal{A}' = 0.04$ everywhere in this first version. The second acknowledges differences in volatility across countries but continues to assume away overprecision. We let σ and $\mathcal{A}'$ differ across countries based on the data but force $\tilde{\sigma} = \sigma$. The third version runs the full exercise, fitting differences in uncertainty, volatility, common shocks, and GDP per capita from Table 6.

Table 8 reports the parameters that come out of the three versions of the accounting exercise, with Table 8a corresponding to the first, 8b to the second, and 8c to the third (full) exercise. Table 8c also reports the degree of overprecision implied by our facts, expressed as a ratio between the subjective and objective volatility parameters ($\tilde{\sigma}/\sigma$). At higher levels of GDP per capita that ratio is lower, which confirms our reasoning from Section 3 that overprecision is more severe in richer countries. This pattern emerges even though our model allows for common shocks $\mathcal{A}'$ that match the contribution of bias in mean squared forecast errors implied by Figure 4b. Thus, our quantitative exercises rule out large country-level shocks as the primary driver of our overprecision statistics.

To find out whether uncertainty and volatility help us explain GDP per capita gaps, Figure 5 plots the relative TFP shifters that come out of each exercise against relative GDP per capita.[16] The red circles correspond to the first version of our accounting exercises

[16]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 we that we care more about the ability to generate value

Table 8: **Accounting Exercises: Calibrated Parameters**

(a) **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	0.62	0.35	0.16
f	Fixed cost	30.3	15.5	7.1	2.4
σ	Objective volatility	0.28	0.28	0.28	0.28
$\mathcal{A}$	Common shock to sales	0.04	0.04	0.04	0.04

(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	0.56	0.27	0.09
f	Fixed cost	30.3	13.5	4.9	1.3
σ	Objective volatility	0.28	0.36	0.45	0.61
$\mathcal{A}$	Common shock to sales	0.04	0.09	0.16	0.26

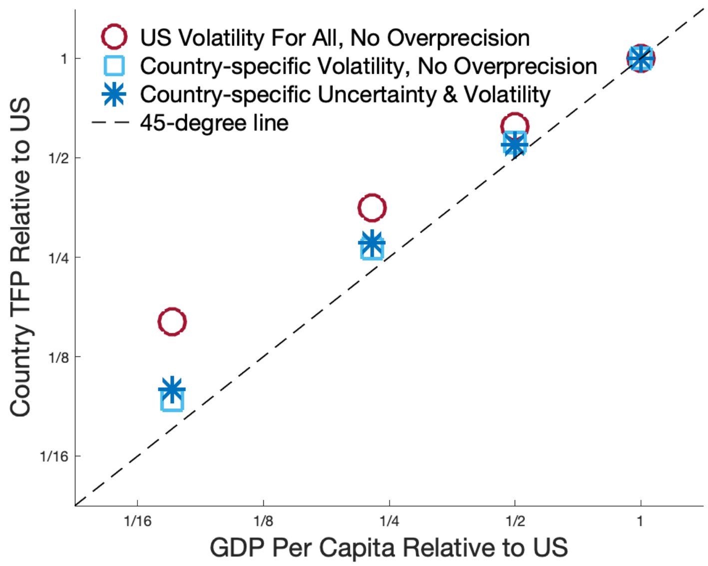
(c) **Full Exercise: Country-Specific Volatility, Uncertainty, and Bias^2/MSE**

Parameter	Description	Relative GDP per Capita: 1.00	0.50	0.23	0.08
$\hat{A}$	Relative TFP	1.00	0.55	0.28	0.10
f	Fixed cost	11.0	3.9	1.1	0.2
$\tilde{\sigma}$	Subjective volatility	0.05	0.10	0.17	0.27
σ	Objective volatility	0.28	0.36	0.46	0.61
$\mathcal{A}$	Common shock to sales	0.04	0.09	0.16	0.25
$\tilde{\sigma}/\sigma$	Overprecision ratio	0.18	0.28	0.36	0.44

Notes: This table shows the parameters that match the four data moments for three versions of our development accounting exercise. The version in Table 8a 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). The version in Table 8b 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. Table 8c 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.

that abstracts from our facts. The light blue squares come from the second, which adds differences in volatility and common shocks. The blue asterisks correspond to the third version matching all our targets.

Figure 5: **Relative TFP vs. GDP Per Capita**



Notes: We plot the relative TFP parameters from three versions of our development accounting exercise against relative GDP per capita. See Table 8 for more details. See Table 6 for more about the relative GDP per capita statistics that we target.

Figure 5 shows two key results:

1. We infer *lower* TFP in developing/emerging economies when we match their higher levels of realized sales volatility. In the figure, the light blue squares are below the red circles for each of the middle- and lower-income countries. Both the squares and circles abstract from overprecision, but the circles also abstract from cross-country differences in volatility and bias squared to mean squared error ratios.

2. We infer *higher* TFP in developing/emerging economies when we let managers be overprecise by matching both the level of uncertainty and volatility in each country. In the figure, the blue asterisks that come from the full accounting exercise are above the light blue squares, except at relative GDP per capita of 0.5. For that country, on the border between emerging and advanced economies, overprecision matters little for implied TFP.

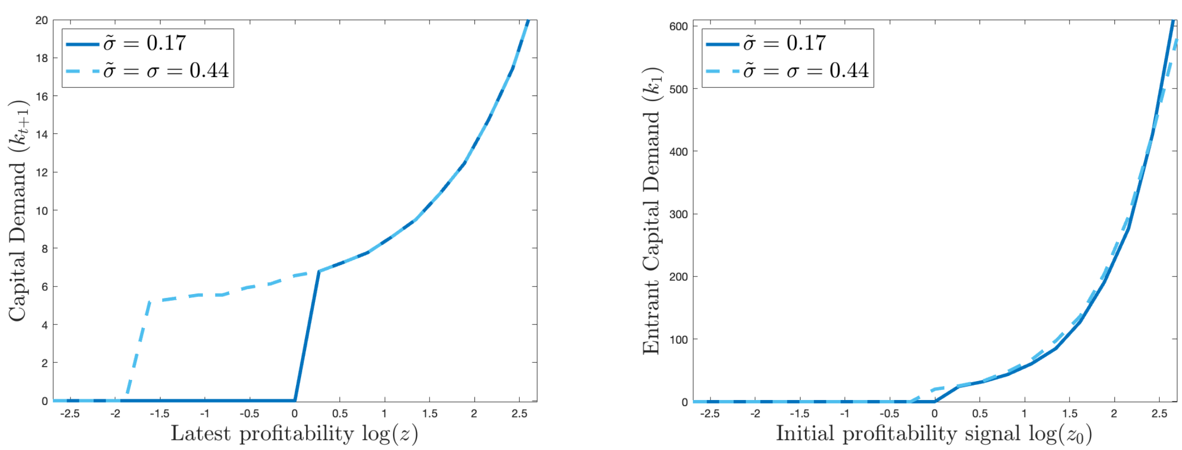
added than variable profits across countries. That said, there is a one-to-one mapping between $\hat{A}$ and A that depends only on fixed parameters and the equilibrium wage. See the discussion in Section 4.1.

Altogether, our facts imply lower TFP in developing/emerging economies than if we were to ignore the evidence on cross-country uncertainty and volatility. Compare the asterisks that match all our facts from Section 3 and the circles that assume uniformly low uncertainty and volatility everywhere. But the implications are bigger for poor countries. At a relative GDP per capita of 0.5, our facts depress implied TFP by 12%. That number doubles and trebles to 22% and 38% at relative GDP per capita of 0.23 and 0.08, respectively.

Two opposing effects are behind the patterns in Figure 5. The first is an Oi-Hartman-Abel or volatility effect that brings growth and investment opportunities when there is high volatility (see Oi, 1961; Hartman, 1972; Abel, 1983). Managers' demand for capital is convex in log-profitability ($\log(z)$) except when the manager chooses to liquidate the firm and capital demand goes to zero, as Figure 6 shows. This convexity is a general feature of models with decreasing returns to scale and persistent profitability.[17] An increase in σ (the volatility of $\log(z)$), thus, raises the probability of large investment opportunities. It also raises firm value, as Figure A.8 shows in the appendix. An economy with sustained volatility guarantees *some* firms will become highly profitable and will want to grow and invest. Other things equal, that leads to capital accumulation and higher GDP per capita under high volatility.

Figure 6: **Demand for Capital is Convex in Profitability**

(a) **Incumbents** (b) **Entrants**



Notes: The figures show capital demand (imputed to zero when managers choose to liquidate the firm or remain out of the market), 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.

[17] 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 $\alpha \in (0,1)$.

The second effect arises because overprecise managers *undervalue* the firm's real options. Unwinding investments is costly ($\gamma = 0.3$ yields a loss of 30% when disposing of invested capital), so managers value the (call or put) option to 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). They also value the put option that lets them remain in the market today and collect the liquidation value of capital, $(1-\gamma)k$ if profitability deteriorates in the future. All of these real options gain value from volatility just as financial call and put options do.

Overprecise managers underestimate the volatility of $\log(z)$ and therefore *undervalue* their real options. They do less waiting before investing or disinvesting, and liquidate the firm at the first sign of weak profitability. We can see some of these dynamics in Figures 6 and A.8. Managers perceiving lower volatility demand zero capital sooner as we move left along the profitability $\log(z)$ axis and they undervalue the firm when they perceive less uncertainty. Thus, economies with overprecise managers reallocate capital more readily towards profitable enterprises and away from unprofitable ones, as Barrero (2022) notes. That boost to reallocation raises GDP per capita for a given TFP shifter A.[18]

Our empirical facts from Section 3 create a horse race between the volatility (Oi-Hartman-Abel) and overprecision effects. High volatility in poor countries brings growth and investment opportunities to some lucky firms there. But volatility-driven capital accumulation is at odds with volatile countries' being poor, so we need *lower* TFP shifters to reconcile their high volatility and low GDP per capita. High uncertainty and modest overprecision in poor countries, instead, slows reallocation and drags down their GDP per capita relative to rich countries', whose highly overprecise managers reallocate capital swiftly. We infer *higher* TFP shifters in developing/emerging economies because differences in overprecision help us explain why poor countries lag behind. Indeed, TFP gaps can be smaller when differential overprecision explains why poor countries remain so.

Ultimately, Figure 5 and Table 8 say that the volatility effect wins the horse race in our quantified model. The investment opportunities that high volatility brings to poor countries push down those countries' TFP shifters more than their low overprecision and sluggish reallocation push them up.[19]

[18]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 (seeBento and Restuccia, 2017 and David and Venkateswaran, 2019) limit the scope of static misallocation in our model.

[19]An alternative exercise asks, how would GDP per capita in the developing world change if we gave it US-level uncertainty $\tilde{\sigma}$ and volatility σ? Consistent with our headline results, we estimate reductions of up to 80% in the country with relative GDP per capita of 0.08 under this exercise. Giving those countries

5.3 Robustness

How do our conclusions about the absolute and relative magnitudes of the volatility and differential overprecision effects depend on the structure and parameterization of the model we use to run our development accounting exercises? Table 9 reports our main results when we run our accounting exercises separately for eight specifications of the model. Because our framework is simple (it only has two state variables and one control variable) and our quantitative exercises look for an exactly-identified mapping between key parameters and moments, it is inexpensive in terms of time and computation to consider additional specifications.

For each of the three hypothetical developing/emerging economies in the exercise, Table 9 shows the change in relative TFP that we infer if we match all of our key facts on uncertainty and volatility (columns 2 to 4 of Table 6) compared with assuming there is no overprecision and that volatility and common shocks in all countries are as large as in the high income country. For the baseline model in row (1) that means taking the percent change in relative TFP $\hat{A}$ from Table 8a to Table 8c, or comparing the asterisks and circles in Figure 5. Table A.10 in the appendix isolates the impact of differential overprecision in each specification, comparing $\hat{A}$ across the equivalent of Tables 8b and 8a, or the blue squares and asterisks in Figure 5.

Part of the dominance of the volatility effect in our main results comes from our assumption of a log-Normal autoregressive process for profitability z (see equations 6 and 5). This assumption is standard and empirically consistent with the shape of firm size and profitability distributions in many firm-level datasets. But it yields higher mean realized z under high volatility via a Jensen's inequality effect, pushing down our inferred TFP $\hat{A}$ in high-volatility poor countries. Managerial expectations of future z could be similarly swayed by a Jensen's effect; specifically, overprecision ($\tilde{\sigma} < \sigma$) could depress managerial expectations $\widetilde{\mathbf{E}}[z]$, leading under-investment and pushing up our TFP estimates. The second row of Table 9 shows how our results change when we adjust for both of these effects. We obtain smaller results—14.6% lower in TFP for the country with relative GDP per capita of 0.08—because the effect on realized z is stronger. But the volatility effect dominates, as in our baseline specification. We opt not to adjust for these Jensen's effects by default because we think they might be a feature rather than a bug of our framework. They imply more fat-tailed firm-size distributions in developing countries. That is consistent with a few large firms dominating markets, and with evidence of greater log-productivity dispersion in emerging economies, as documented by Ayerst et al. (2024).

US levels of overprecision, but keeping their high volatility instead raises GDP per capita by nearly 60% by boosting reallocation.

Table 9: Δ **Inferred Relative TFP (%) Implied by Uncertainty & Volatility Facts**

		Rel. GDP per Capita		
Model	**Description of Specification**	**0.50**	**0.23**	**0.08**
(1)	Baseline (see Tables 6, 7, and 8 and Figure 5)	-11.7	-21.5	-37.8
(2)	Adjust for Jensen's effect on z	-4.2	-9.2	-14.6
(3)	No common shocks to output ($\mathcal{A}' = 0$)	-10.9	- 24.5	-47.1
(4)	No cost of external finance ($\psi = 0$, $\psi_e = 0$)	-10.3	-22.3	-40.4
(5)	No entry/exit decision	-6.3	-15.2	-31.7
(6)	No cost of external finance ($\psi = 0$, $\psi_e = 0$) or entry/exit	-7.4	-18.8	-38.2
(7)	Frictionless investment ($\psi = 0$, $\psi_e = 0$, $\gamma = 0$), no entry/exit	-16.0	-37.8	-61.7
(8)	Lower persistence of z ($\rho = 0.8$ instead of $\rho = 0.9$)	-4.7	-11.7	-19.1

Notes: For each hypothetical country with relative GDP per capita of 0.50, 0.23, and 0.08, we report the change in relative TFP $\hat{A}$ we obtain from our accounting exercise that matches all of our key facts about uncertainty and volatility (columns 2 to 4 of Table 6) instead of assuming there is no overprecision and volatility and common shocks in all countries are the same as in the country with relative GDP per capita of 1.00. Row (1) reports results from our baseline specification with fixed parameters reported Table 7 and calibrated parameters in Table 8. Row (2) adjusts managerial expectations in each country upward by $\exp(\sigma^2/2 - \tilde{\sigma}^2/2)$ 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 accounting exercises ignoring the evidence about forecast error bias and mean squared forecast errors in Figure 4b. Row (4) considers a specification of the model with no cost of external finance for incumbents ($\psi = 0$) or entrants ($\psi_e = 0$). Row (5) abstracts from entry and exit (liquidation) dynamics by targeting an exit rate of zero and setting fixed costs of operation f to zero. Row (6) abstracts from exit as well as financing costs, combining (4) and (5). Row (7) removes all frictions to investment other than a one period time-to-build constraint, abstracts from entry/exit dynamics, and adjusts managerial expectations of future z downward by a factor of $\exp(\tilde{\sigma}^2/2)$. Finally, row (8) uses the baseline parameterization but lowers the persistence of $\log(z)$ to 0.8 per half-year.

Next, we consider five specifications of our model that remove features of our baseline specification. None of them are critical to our results. We find modestly larger effects in row (3) when we abstract from common shocks to output in each country by setting $\mathcal{A}' = 0$ and ignoring the evidence about bias squared to mean squared forecast error ratios from Figure 4b. Because those ratios are larger in poor countries, ignoring that evidence requires larger idiosyncratic volatility σ to fit poor countries' average volatility (absolute forecast errors). And larger σ implies stronger volatility effects.

Our results change little in row (4) when we set the cost of external finance for incumbents ψ and entrants ψ_e to zero. In the baseline specification, these parameters constrain managers from investing purely out of a signal of high profitability. They smooth investment responses to upside shocks and could limit the positive effects of high volatility on investment and output. However, when we remove those frictions we obtain changes in inferred TFP that are similar to those in the baseline specification in row (1).

The specifications in rows (5) and (6) test whether our results change when we remove managers' ability to liquidate the firm. In both rows obtain an exit rate of zero by setting the fixed operating cost $f = 0$, but in row (5) we keep the external financing costs at their baseline level and set them to zero in row (6). The results are, at best, modestly smaller than in the baseline. Thus, the relative strength of the volatility and uncertainty effects is similar if managers can only shrink but not liquidate the firm in response to bad profitability.

Row (7) considers a stripped-down version of our model. It abstracts from the entry/exit margin and from all frictions to investment other than a standard time-to-build constraint (choose k' today before knowing z'). Managers choose k' each period to equate their expectation of the future marginal profitability of capital $\alpha\tilde{\mathbf{E}}[z'|z]Ak'^{\alpha-1}$ and its user cost $r+\delta$.[20] Thus, managers face no real options but still have convex demand for capital. Our results about TFP are about twice as large in row (7) as in the baseline case because the lack of frictions supercharges the volatility effect. Managers, after all, are free to respond to shocks and have no incentive or constraint to adjust the firm's capital slowly.

Finally, row (8) of Table 9 shows how the persistence of profitability matters greatly for the strength of the volatility effect. If a right-tail shock to profitability z is transitory, managers have little incentive to invest and grow in response. High volatility leads to less capital accumulation and lower GDP per capita when we lower the persistence ρ to 0.8 from 0.9 in the baseline specification. Thus, we get about half as large of an impact on inferred TFP in specification (8) as in the baseline.

Our conclusion from Table 9 is that cross-country uncertainty and volatility matter across a class of models that nests our baseline specification. Abstracting from investment frictions long recognized by the literature on investment (e.g., see Cooper and Haltiwanger, 2006) yields much larger results, whereas assuming less persistent profitability or stripping out Jensen's inequality effects yields smaller ones. But in all cases the volatility effect on firm investment dominates. We always end up inferring lower TFP in developing/emerging economies to reconcile their high volatility and low GDP per capita.

6. Discussion

The TFP shifters in our model act as a residual for relative GDP per capita, conditional on uncertainty, volatility, and the broader structure of the model. We infer lower TFP in developing/emerging economies when we match our facts; specifically, to explain why their managers don't invest and accumulate capital when investment opportunities (created by high volatility) arrive. Thus, our TFP results point to economic forces that constrain investment in poor countries but not rich ones. They challenge the view that high uncertainty and volatility, on their own, explain why poor countries lag behind in

[20]Because expected profitability $\tilde{\mathbf{E}}[z'|z]$ is a first-order determinant of investment in this specification, our estimates for model (7) adjust managerial expectations of future z' downward by a factor of $\exp(\tilde{\sigma}^2/2)$ to prevent them from investing purely out of the Jensen's effect of volatility on expected z'.

terms of productivity and GDP per capita.

Our paper's main limitation is an inability to estimate different frictions or fundamentals beyond TFP, uncertainty, and volatility across rich and poor countries. Filling that gap, by quantifying and pinning down the forces that hold back poor countries should be a priority of future research. Indeed, the key lesson of Table 9 is that the nature and strength of investment frictions matters modestly if those frictions are similar across poor and rich countries. Policy prescriptions will also depend on the nature and strength of those forces.

Many of the forces that could restrain investment in poor countries are financial. David et al. (2014) and Falk et al. (2018) argue that the opportunity cost of capital in poor countries is higher than in rich ones, respectively, due to higher risk premiums and impatience. Thus, poor-country managers need stronger cash flows to justify a given investment opportunity. Weak financial markets and frictions to capital reallocation could act similarly. Eisfeldt and Rampini (2006) argue that capital illiquidity—contractual and informational frictions that prevent transactions—rises in recessions. If those frictions are persistently high in poor countries, they could contribute to depressed investment and reallocation. Lack of access to outside finance could also compound the negative effects of uncertainty on investment and reallocation. Vereshchagina (2022) shows risk-averse entrepreneurs have fewer incentives to invest in their firm's productivity in high-volatility poor countries. Hard-to-access financing amplifies that effect.

But other fundamental differences between rich and poor countries could also explain why high volatility doesn't lead to investment in the latter. The eighth row of Table 9 shows how the volatility effect weakens when shocks become transitory and less worth responding to in all countries. If those shocks are especially transitory in poor countries, that would further weaken the link between volatility and investment there. So would lower returns to scale, for example due to delegation constraints that restrain firm growth, as Bloom et al. (2012) and Akcigit et al. (2021) suggest. And that is even before considering distortions to resource allocation and firm operations that are canonically more severe in poor countries (see, e.g., Hsieh and Klenow, 2009, Bartelsman et al., 2013, Bento and Restuccia, 2017.)

Negatively skewed shocks in developing countries could explain why they don't accumulate capital under high cash flow volatility, but we find little evidence for this mechanism in our data. Figure A.6 in the appendix shows average forecast errors are about flat with GDP per capita. Combined with poor countries' higher volatility, that pattern doesn't suggest that sales shocks are more negatively skewed there. The figure also shows little correlation between the first and second moments of the forecast error distribution, which we would expect if shocks were skewed in high-volatility countries. Altogether, we find little evidence of differential skewness across countries, or of negative skewness more generally.

A long literature following Bloom (2009) and Fernández-Villaverde et al. (2011), among others, suggests that uncertainty is bad for economic outcomes. At first glance our paper says the opposite, namely that volatility is good and countries benefit from heightened uncertainty. But our findings are fully consistent with prior work linking uncertainty to lower investment and output over the business cycle. 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. Modest overprecision in poor countries depresses reallocation and holds down output precisely by freezing investment.

The key difference between our work and the prior literature is our focus on stationary, long-run equilibriums by country. As Bloom (2014) notes, positive volatility (Oi-Hartman-Abel) effects are typically weak in the short run and stronger in the long run. Sustained, long-run volatility is what guarantees *some* firms receive highly profitable investment opportunities in our model and leads to a dominant volatility effect. The conventional narrative applies better to short-lived volatility shocks that freeze investment temporarily. But Bloom (2009) shows how such shocks can lead to a rebound in output and investment as *some* firms eventually receive positive shocks that push them out of their inaction. That rebound is a time-series analogue to our volatility effect.

If poor countries had sustained uncertainty without sustained volatility, that would depress investment and output in the long run. But that's not what we see in our data. High uncertainty in poor countries is accompanied by high cash flow volatility. In our model, that volatility is what brings investment opportunities and implies lower TFP to explain why poor-country managers don't take them up. Reversing that result will require researchers to identify specific forces, financial or fundamental, that restrain investment in poor countries but not rich ones.

7. Concluding remarks

Our paper makes two key contributions to the literature on business uncertainty, volatility, and their impact on capital budgeting. First, we document new facts about uncertainty in high- and low-volatility environments by surveying over 31,000 managers across 41 countries. We show subjective uncertainty about future sales and its realized volatility both decline with GDP per capita. Managers underestimate volatility in all countries where we can measure both (they are *overprecise*), but disproportionately so in low-volatility rich countries. That means rich-country managers tune out more of the little volatility they are exposed to. We establish these facts from managers' viewpoints and information sets.

Thus, poor-country firms are subject to more *unforecastable* cash flow risk, and managers recognize it. Greater volatility in poor-country data is not simply due to high measurement error or macro volatility.

Second, we build a dynamic model with convex demand for capital and real investment options to quantify the implications of our facts. We model high- and low-volatility countries based on our cross-country evidence and ask, how much do differences in uncertainty and volatility matter for investment and reallocation? To find out, we run development accounting exercises (see Caselli, 2005 and Hsieh and Klenow, 2010) and weigh up our facts by how much they change our inference about aggregate TFP.

High volatility in poor countries creates a puzzle, because it generates growth and investment opportunities. Reconciling those opportunities with poor countries' low GDP per capita requires lower TFP there. Modest overprecision and high uncertainty instead drags reallocation and output in poor countries, raising their implied TFP. We consider eight model specifications and always find the volatility effect dominates. Thus, for a country with $5,000 GDP per capita in 2019 (similar to Kenya), our facts imply 30 to 40% lower TFP in our preferred specifications, and 15% in the most conservative case. That means high uncertainty and volatility cannot, on their own, explain why poor countries lag behind. They must come alongside other forces that depress investment and TFP. We cannot identify those other forces, which may include weak financial markets, high costs of reallocation, risk premiums, or transitory business fluctuations. We can only ask how much each of them matters when combined with high uncertainty and volatility in developing and emerging economies.

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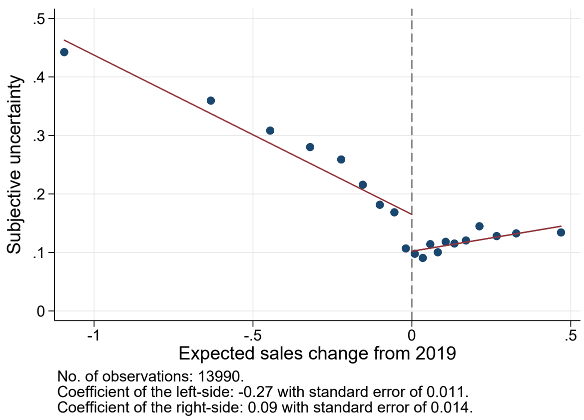
Internet Appendix — Not Intended for Publication

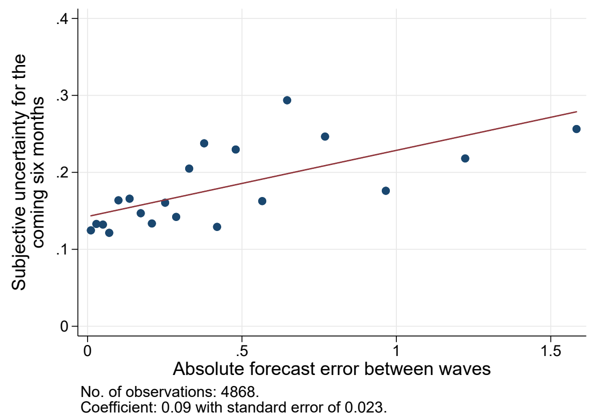
A. Additional results

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

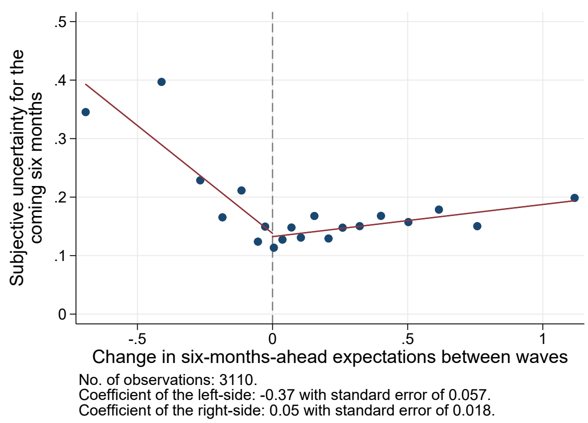
(a) Subjective uncertainty has a negative correlation with expected sales.



(b) Uncertainty rises with past absolute forecast errors.



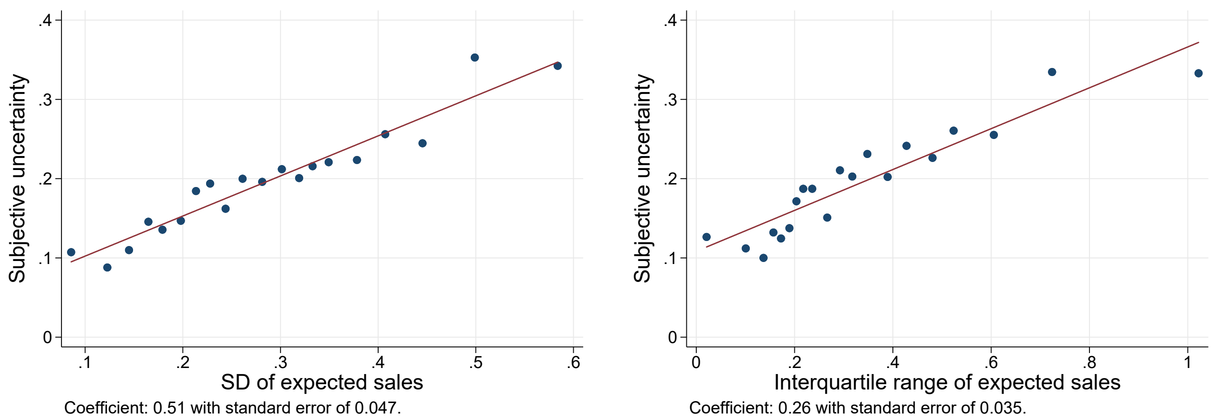
(c) Uncertainty is v-shaped in revisions to expected sales.



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**

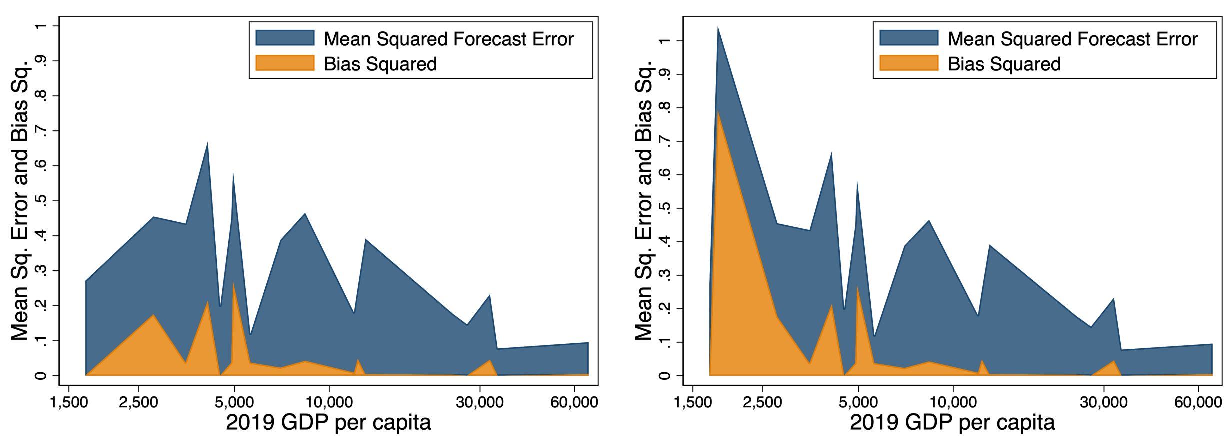
(a) Standard deviation of expected sales growth. (b) Interquartile range of expected sales growth.



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)

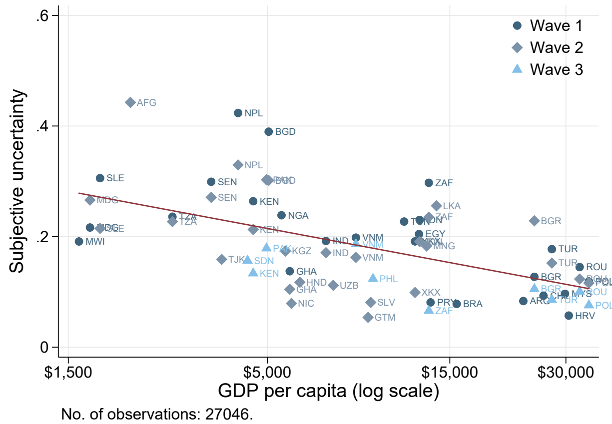


Notes: In both charts we plot the mean squared forecast error and bias squared by country against 2019 GDP per capita. The left chart uses our main sample that excludes Sierra Leone, while the right chart adds Sierra Leone. We compute absolute forecast errors as the absolute difference between realized 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.

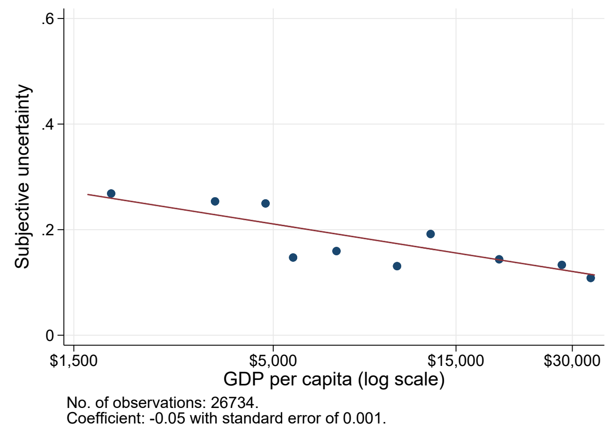
Figure A.4: **Uncertainty and Volatility Decline with GDP per Capita**

Uncertainty vs. GDP per Capita

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

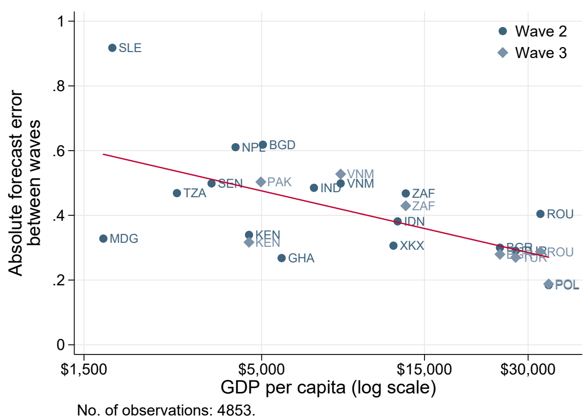


(b) **Controls for Firm Size, Sector, and Quarter**

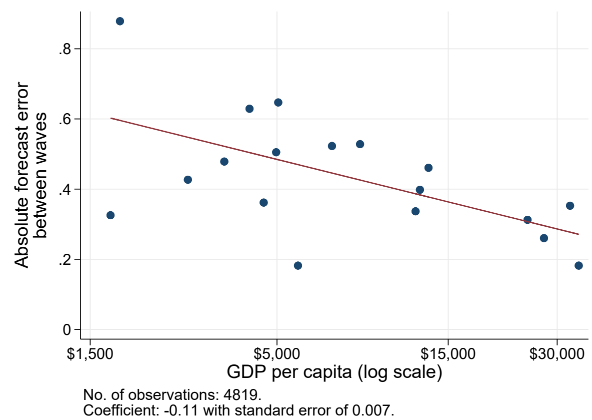


Volatility (Absolute Forecast Errors) vs. GDP per Capita

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

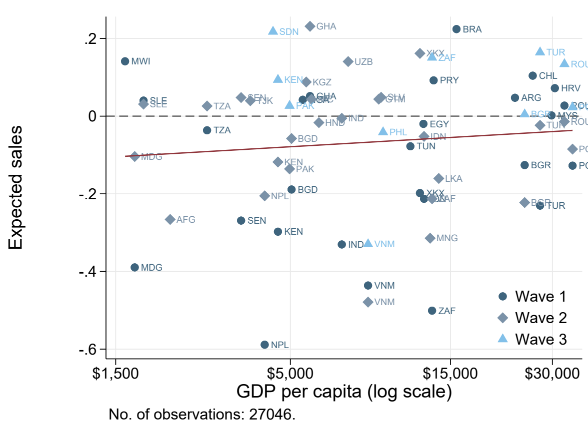


(d) **Controls for Firm Size, Sector, and Quarter**

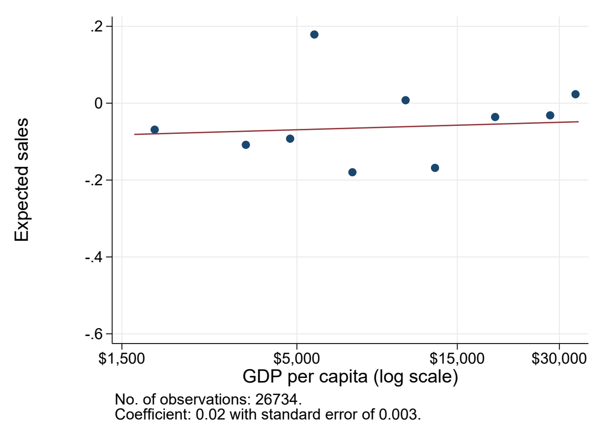


Expected Sales vs. GDP per Capita

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



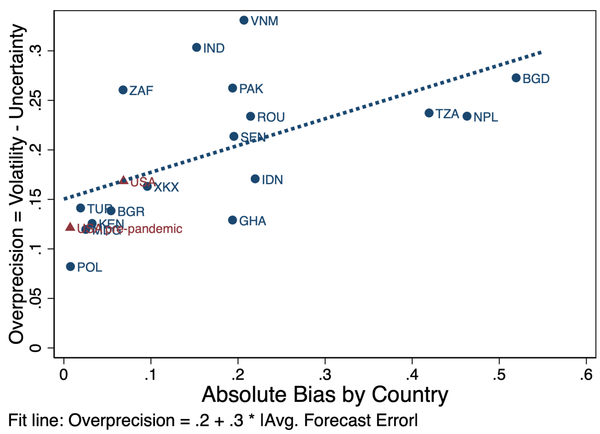
(f) **Controls for Firm Size, Sector, and Quarter**



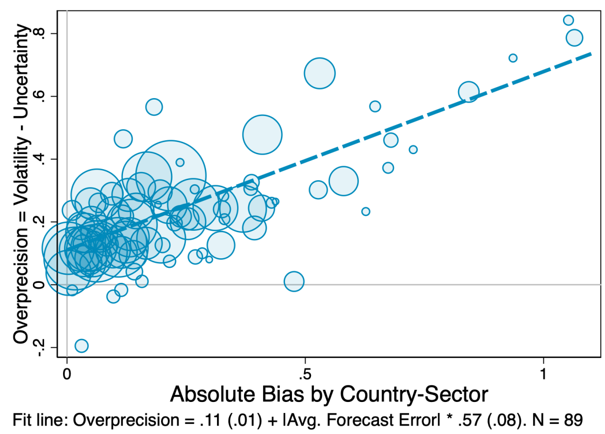
Notes: The vertical axis shows employment-weighted averages across firms by country-wave (left panels) and in the binned scatter plot (right panels). Panels (a) and (b) have subjective uncertainty about six-months-ahead sales on the vertical axis; panels (c) and (d) have volatility (absolute forecast 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: **Overprecision Exists Even When Country-level Bias (Common Shocks) Are Near Zero**

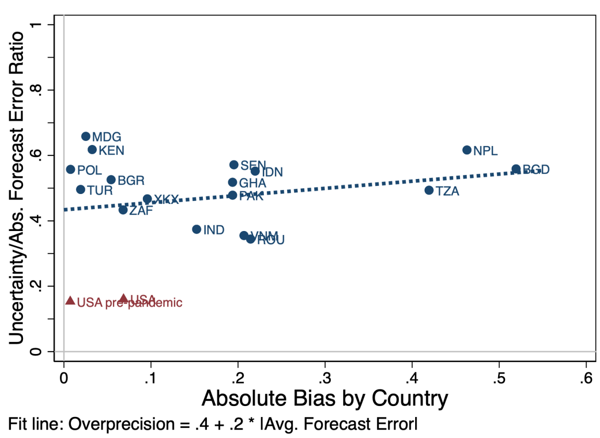
(a) **Across Countries, Overprecision as a Difference**



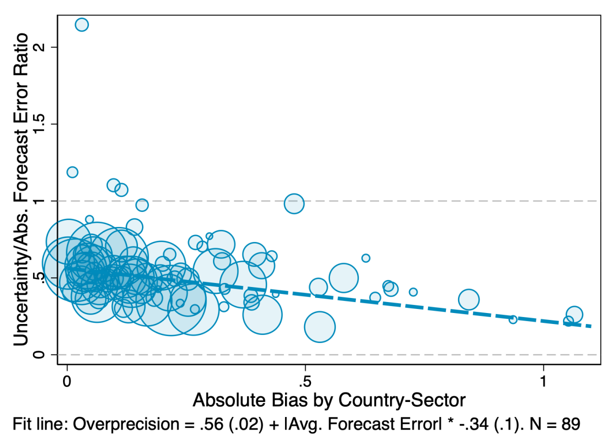
(b) **Across Country-Sectors, Overprecision as a Difference**



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



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

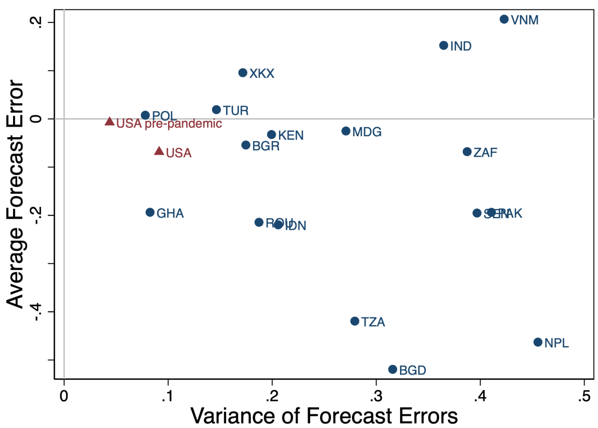


Notes: In each chart we plot a measure of overprecision against absolute bias (a measure of the common shock across firms). The charts on the left use country-level and those on the right country-sector-level averages. The top charts measure overprecision as the difference between average volatility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

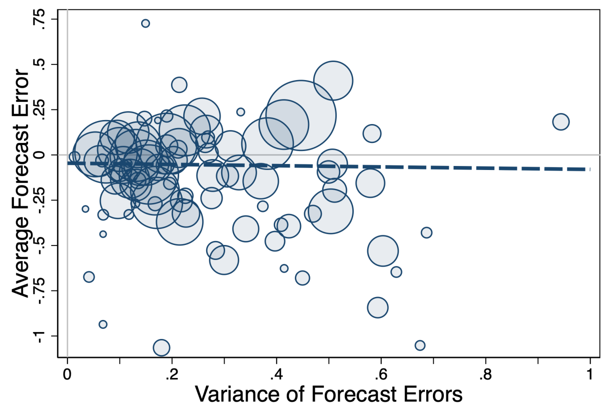
Figure A.6: **Average Forecast Errors (Bias) Don't Correlate Strongly with Forecast Error Variance or GDP per Capita**

Average vs. Variance of Forecast Errors

(a) **Across Countries**



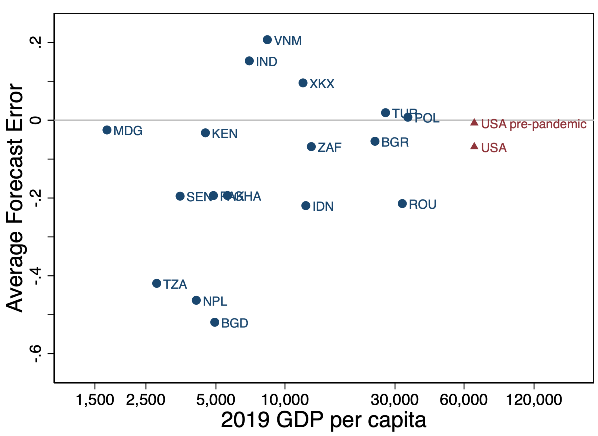
(b) **Across Country-Sectors**



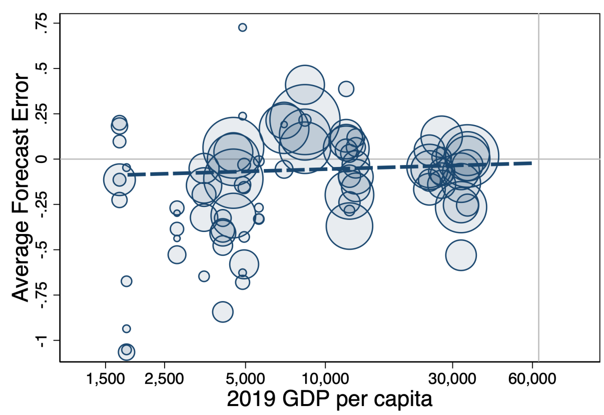
Fit line: Avg. Fcast Error = -.05 (.05) + Variance of Fcast Errors. * -.03 (.24) . N = 89

Average Forecast Error vs. GDP per Capita

(c) **Across Countries**



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

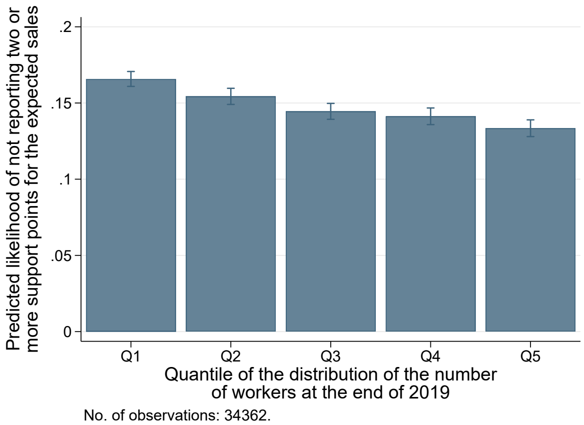


Fit line: Avg. Fcast Error = -.22 (.26) + log(GDP per Capita) * .02 (.03) . N = 89

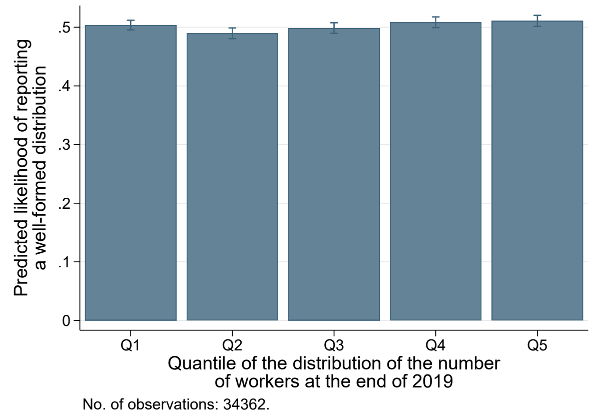
Notes: In the top panels, we compute employment-weighted averages and variances of forecast errors by country (left) and country-sector (right) and plot them against each other. In the bottom panels we plot average forecast errors against 2019 PPP GDP per capita by country (left) and country-sector (right).

Figure A.7: **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.



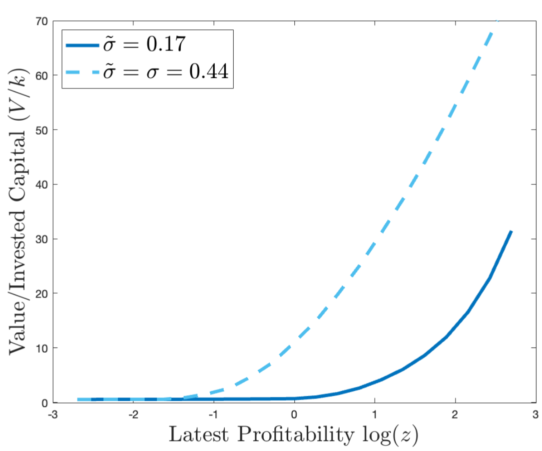
(b) Average predicted likelihood of reporting well-formed subjective distributions for each quantile of the firm size distribution.



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.8: **Firm Value is Convex in Profitability**

(a) **Incumbent Value**



(b) **Entrant Value**

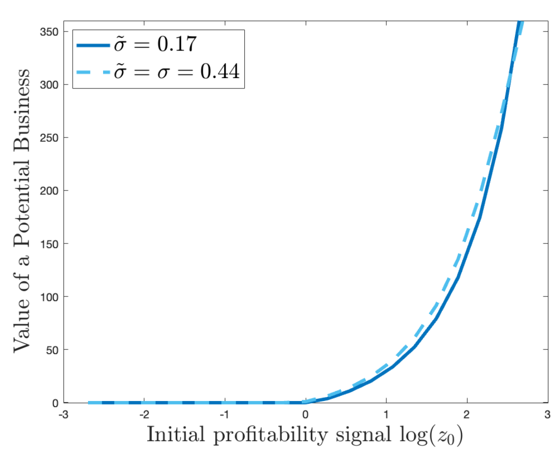


Table A.1: **Uncertainty Declines with GDP per Capita: Trust, Corruption, Women Leaders, and Exporters**

	(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.2: **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.3: **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.4: **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.5: **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.6: **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.7: **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.8: **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.9: **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.

Table A.10: **Δ Inferred Relative TFP (%) Due to the Uncertainty (Real-Options-Undervaluation) Effect, Across Model Specifications**

		Rel. GDP per Capita		
Model	**Description of Specification**	**0.50**	**0.23**	**0.08**
(1)	Baseline (see Tables 6, 7, and 8 & Figure 5)	-1.5	3.8	7.6
(2)	Adjust for Jensen's effect on z	-0.7	3.1	1.5
(3)	No common shocks to output ($\mathcal{A}' = 0$)	1.2	3.5	12.0
(4)	No cost of external finance ($\psi = 0$, $\psi_e = 0$)	-0.6	1.2	5.8
(5)	No entry/exit decision	1.5	3.2	5.1
(6)	No cost of external finance ($\psi = 0$, $\psi_e = 0$) or entry/exit	1.8	3.3	5.5
(7)	Frictionless investment ($\psi = 0$, $\psi_e = 0$, $\gamma = 0$), no entry/exit	-0.2	-0.0	8.1
(8)	Lower persistence of z ($\rho = 0.8$ instead of $\rho = 0.9$)	1.0	2.6	8.3

Notes: For each hypothetical country with relative GDP per capita of 0.50, 0.23, and 0.08, we report the change in inferred TFP $\hat{A}$ we obtain from our accounting exercise that matches differences in volatility across countries but assumes away overprecision instead of matching all of our facts about uncertainty and volatility across countries (columns 2 to 4 of Table 6). Row (1) reports results from our baseline specification with fixed parameters reported Table 7 and calibrated parameters in Table 8. Row (2) adjusts managerial expectations in each country downward by $\exp(\tilde{\sigma}^2/2)$ and gross profit TFP A up by $\exp(\sigma^2/2)$ to remove any effects of high uncertainty or volatility on expected z' due to its log-Normality and Jensen's inequality. Row (3) sets all common shocks $\mathcal{A}'$ to zero and runs the accounting exercises ignoring the evidence about forecast error bias and mean squared forecast errors in Figure 4b. Row (4) considers a specification of the model with no cost of external finance for incumbents ($\psi = 0$) or entrants ($\psi_e = 0$). Row (5) abstracts from entry and exit (liquidation) dynamics by targeting an exit rate of zero and setting fixed costs of operation f to zero. Row (6) abstracts from exit as well as financing costs, combining (4) and (5). Row (7) removes all frictions to investment other than a one period time-to-build constraint, abstracts from entry/exit dynamics, and adjusts managerial expectations of future z downward by a factor of $\exp(\tilde{\sigma}^2/2)$. Finally, row (8) uses the baseline parameterization but lowers the persistence of $\log(z)$ to 0.8 per half-year.

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**

		Percent of responses							
	N	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.