# Business Uncertainty in Developing and Emerging Economies*

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**Abstract**

We study business uncertainty in volatile environments by surveying 31,000 managers across 41 countries and building a dynamic model to quantify the implications. We elicit subjective probability distributions about future own-firm sales and measure firm-level uncertainty with their second moments. In turn, we measure realized volatility at the firm-level with managers' absolute forecast errors. Our analysis centers on two new facts. (1) Uncertainty and volatility both decline with GDP per capita. (2) Managers underestimate volatility everywhere (they are *overprecise*), but more so in rich countries. We build a heterogeneous-firm dynamic model featuring real investment and entry/exit options, and use it to weigh up our facts against cross-country productivity gaps. Firm value and investment are convex in profitability, so high volatility in poor countries requires lower aggregate TFP to account for their low GDP per capita. High overprecision in rich countries pushes the other way because it improves selection and reallocation, thereby raising rich-country GDP per capita.

**JEL classification:** D84, G31, G32, E22, E23, O11, D24, C81

**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 might those perceptions impact investment and entrepreneurship in the presence of real investment, entry, and exit options? These are fundamental and challenging questions in corporate finance and macroeconomics. To start, subjective uncertainty – as perceived by managers over future firm outcomes – is not easily observable. Proxies based on realized or implied volatility of stock returns and sales growth are readily available, but they differ systematically from survey-based measures that ask managers about potential outcomes and their probabilities (e.g., see Boutros et al., 2020; Barrero, 2022). When we do have measures of firm-level subjective uncertainty, they cover a few advanced economies where uncertainty levels are usually low, spiking up around recessions. Many of those datasets date from the mid-2010s and cover just one major spike at the start of the pandemic in 2020 (e.g., Bachmann et al., 2020; Altig et al., 2022). Thus, it has been hard to study business uncertainty in volatile environments due to a lack of data from appropriate settings.

We address these challenges by surveying 31,000 managers across 41 countries, measuring firm-level subjective uncertainty and realized volatility (i.e., absolute forecast errors) across a wide range of environments. Aggregating those measures by country and country-sector, we uncover large differences in the way managers perceive and experience uncertainty. We establish new facts about business uncertainty and volatility across countries, and use those empirical patterns to examine the implications for managerial decision-making in high- versus low-volatility regimes. To do so, we build a dynamic model featuring real investment and entry/exit options. Then we ask, how do cross-country differences in uncertainty and volatility change our inference about countries' aggregate TFP by changing investment and entrepreneurial dynamics in the model? Thus, we weigh up our facts against large and well-known productivity gaps across countries.

Our data come from the World Bank's Business Pulse and Enterprise Surveys (BPS and ES), which interviewed managers in dozens of countries across Eastern Europe, Asia, Africa, and Latin America between 2020 and 2022. As part of the surveys, we elicit subjective probability distributions for future own-firm sales at a six-month horizon. Adapting the methodology developed by Altig et al. (2022), those subjective distributions have three support points; namely, a central, an optimistic, and a pessimistic scenario. We compute each manager's forecast or expectation about future sales from the first moment, and measure their uncertainty using the standard deviation of the subjective distribution. We also observe how forecasts and uncertainty line up with future sales in several countries where we field two or three survey waves and re-interview many managers.

Our paper makes two contributions. First, we document several facts about business expectations and uncertainty across firms and countries. Looking across firms, we validate our data by replicating key results from previous studies about managerial forecasts and uncertainty; namely, Altig et al. (2022), Bloom et al. (2020a), and Bachmann et al. (2020). Managers who expect higher future sales at the time of the survey subsequently report higher actual sales, for example. Those who report more uncertainty about future sales go on to make larger absolute forecast errors. Uncertainty is predictably higher when managers report being in a volatile or turbulent environment; for example, after large (positive or negative) shifts in sales.

Managers also seem to act consistently with their expectations and uncertainty. Those who expect higher future sales tend to report higher employment growth at the time of the survey. Higher uncertainty, by contrast, predicts lower employment growth. Our work contributes to a literature that links uncertainty to business decisions (e.g., Bernanke, 1983; Dixit et al., 1994; Abel and Eberly, 1996; Baker et al., 2020), and work that examines managerial expectations and beliefs as a determinant of firm outcomes (e.g., Guiso and Parigi, 1999; Malmendier and Tate, 2005; Coibion, Gorodnichenko, and Ropele, 2020; and Kumar, Gorodnichenko, and Coibion, 2022).

Our key empirical contribution, however, concerns two new facts about business uncertainty and volatility across countries. First, we show uncertainty and volatility both decline with GDP per capita, as Figure 1a shows. Managers are systematically more uncertain in poor countries, and rightly so, because sales volatility (measured by the magnitude of absolute forecast errors) is also higher in those countries. These relationships hold when we look at country-level averages, and when we regress firm-level uncertainty and volatility on GDP per capita and many firm- and country-level controls. Among them are firm size, sector, recent shifts in sales, measures of macro volatility, and even measures of the quality of institutions. In Figure 1 and elsewhere in the paper we additionally bring in statistics from the Atlanta Fed Survey of Business Uncertainty (Altig et al., 2022) to confirm the pattern extends to the United States before and after the pandemic.

We cannot establish causal links between uncertainty, volatility and GDP per capita. Rather, our contribution is to show that firm-level sales are systematically more difficult to forecast in poor countries, and that managers with private information about future business prospects agree. That result builds on work by Asker, Collard-Wexler, and De Loecker (2014), who show higher time-series variability for firm productivity in poor countries. We go further by establishing that variability from the viewpoint and information set of managers; that is, using their subjective uncertainty and their absolute forecast errors. We also build on work about macro volatility and development by Koren and Tenreyro (2007).

Our second new fact is that managers in all countries underestimate the volatility of their firm's future sales; namely, they are *overprecise*.[1] Figure 1b plots country-level averages of subjective uncertainty against average absolute forecast errors. If managers had rational expectations (and there were no large common shocks) we would expect uncertainty and absolute forecast errors to line up closely. But for all countries where we can compute both statistics, absolute forecast errors are higher than uncertainty. The same is true in 66 out of 67 country-sectors where we can compute these statistics. Furthermore, we find little evidence that large common shocks drive the pattern in Figure 1b.

Overprecision seems to be more severe (in percentage terms) in rich countries. Figures 1a and 1b both show a consistent gap between uncertainty and absolute forecast errors as we move along the horizontal axis. In rich countries where volatility is lower, that gap accounts for a larger share of the total. Earlier work, including Boutros et al. (2020), find managers to be overprecise in a range of settings and firms. With our cross-country data we show that is also true in developing and emerging economies, and compare the degree of overprecision across countries with very different business environments. Our cross-sectional evidence complements work focusing on the time series dimension; for example, Lochstoer and Muir (2022) argue that investors initially underreact and then overreact to volatility spikes in financial markets.

Our second major contribution is to quantify the implications of our facts about how managers perceive uncertainty in high- versus low-volatility environments. We build a heterogeneous-firm dynamic model featuring real investment and entry/exit options. Following Barrero (2022), we assume managers use a subjective stochastic process to forecast firm profitability, and let the conditional volatility of that subjective process differ from the volatility of shocks hitting the firm. Investment and entrepreneurship decisions depend, therefore, on manager perceptions of uncertainty and on the true volatility.

To find out how much uncertainty and volatility matter, we conduct a series of development accounting exercises (see, e.g., Caselli, 2005; Hsieh and Klenow, 2010) that weigh up our facts against well-known productivity and income gaps across countries. We assume firms operate under the same production technology and investment frictions across countries. Then we ask, how low does a country's aggregate TFP need to be to account for (1) its relative GDP per capita, and (2) our cross-country facts about uncertainty

[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 stochastic process that managers seem to use with the one measured by the econometrician. 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.

and volatility? For example, what do we need to infer about a low-income country's TFP, when we know its firms' sales are highly volatile, and its managers underestimate that volatility less than managers in rich countries?

When poor-country firms are subject to high volatility, we need lower aggregate TFP to account for the country's low GDP per capita. The reason is firm value and investment are convex functions of profitability in our model. Under high volatility, that convexity translates into higher chances of becoming highly profitable, growing, and accumulating capital. That means we need lower aggregate TFP to counter those growth opportunities, compared to a world with uniformly low volatility across countries. We cannot trace a causal link from poor institutions or a weak rule of law to high volatility and low aggregate TFP. But our model suggests that whatever forces raise firm volatility must also lower TFP, if we hope to match the negative relationship between volatility and GDP per capita.

High overprecision in rich countries pushes the other way, because it improves selection and raises reallocation. Overprecise managers underestimate volatility and therefore undervalue their firm's real options. The option to enter or remain in the market, for example, is only valuable to them when it is well in-the-money. So, incumbent firms are more positively selected when managers are overprecise. Such managers also invest and disinvest more readily in response to shocks, because the option to wait is less valuable to them (see, e.g., Abel and Eberly, 1996, and Abel et al., 1996). That raises reallocation in rich countries. Altogether, when rich-country firms are better selected and reallocate capital smoothly, we don't need as low aggregate TFP in poor countries to account for their low GDP per capita.

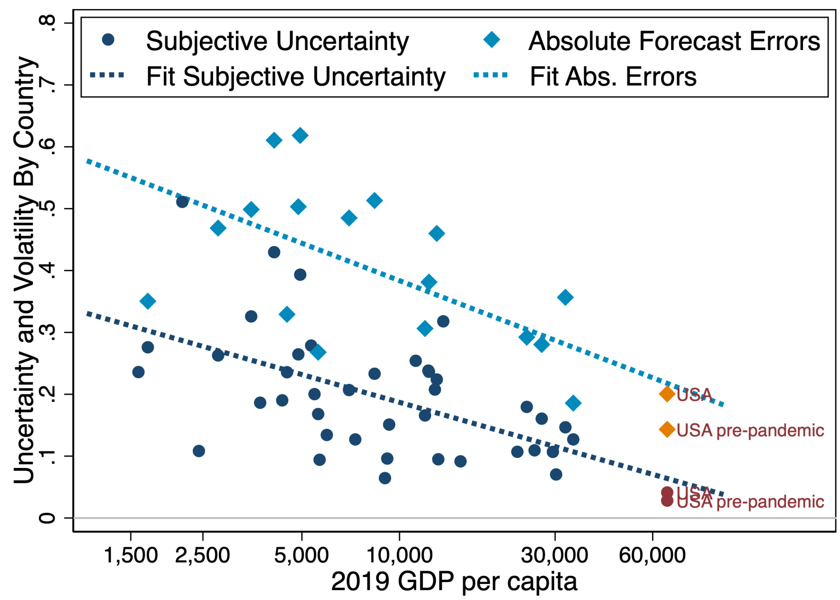
So, how do managers perceive uncertainty in volatile environments? Our evidence from low-income countries shows they report high uncertainty and underestimate the true volatility modestly. Where volatility is lower, as in high-income countries, managers tend to express much less uncertainty than their ex-post forecast errors suggest they should. These patterns can matter a lot when managers face real options and convex payoffs, as our accounting exercises show. Allowing for cross-country differences in uncertainty and volatility can change our inference about aggregate TFP in a low-income country like Kenya by more than a factor of 2.

Our paper contributes to the growing literature that elicits expecations in business surveys. See, for example, the review by Born, Enders, Müller, and Niemann (2021) and the papers cited therein.[2] We show there is much to learn by surveying managers

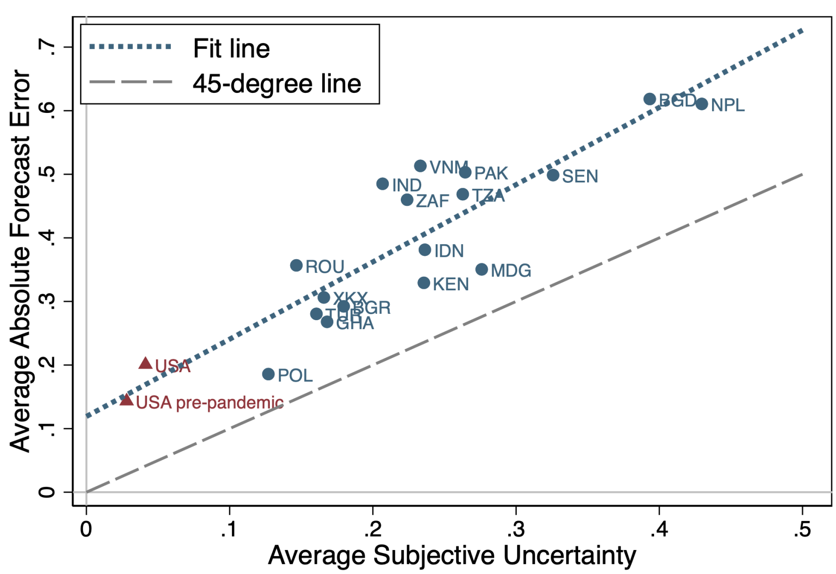
[2] See also Guiso and Parigi (1999); Bachmann et al. (2013); Bachmann et al. (2020); Altig et al. (2022); Bloom et al. (2020a); Coibion et al. (2020); Ma et al. (2020); Andrade et al. (2021); and Meyer, Parker, and Sheng (2021), among others. A separate literature focuses on households. For example,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

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:** The top figure 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). The bottom figure plots employment-weighted average absolute forecast errors (volatility) against subjective uncertainty, both again by country. 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 pre-pandemic data point, respectively.

in developing and emerging economies about future own-firm outcomes. Indeed, we are able to compute firm-level uncertainty for 70% percent of responses to our surveys, compared with 85% in the mandatory US Census survey studied by Bloom et al. (2020a). Statistical agencies, central banks, and research institutions around the world can feasibly use surveys of managers to inform research and policy.

In the rest of the paper, we first provide details about our survey and methodology (Section 2). Then, we validate our measures of business expectations and uncertainty (Section 3) and document our two new facts about uncertainty and volatility across countries (Section 4). We build a dynamic model of heterogeneous firms featuring real options (Section 5), and quantify the implications of our cross-country facts with a series of development accounting exercises (Section 6). Section 7 concludes.

## 2. Surveying business managers in developing and emerging economies

This section describes the World Bank's 2020-2022 Business Pulse and Enterprise Surveys. It also describes the methodology we use to construct measures of expectations and uncertainty about future own-firm sales.

### 2.1 Survey methodology

The World Bank Group Business's Pulse Survey (BPS) and Enterprise Survey (ES) interviewed business managers in over 60 countries between April 2020 and March 2022. The surveys' goal was to gather data on firm operations, sales, employment, and performance in emerging and developing economies after the onset of the COVID-19 pandemic. In most countries, the surveys were conducted in partnership with local statistical agencies, government departments, or business associations that provided know-how and resources enabling the data collection efforts.

To gather the data, the surveys had enumerators conduct telephone interviews with business owners and top managers, conducted in each country's local language. 68% of respondents in our raw data 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 should see Apedo-Amah et al. (2020) for more details about the practical aspects of the data collection.

Our sample in this paper focuses on a subset of 41 countries from all of the World Bank's lending regions where we are able to access the survey microdata remotely.[3] [4] Most

[3]For example, the BPS was implemented in Mexico, but we do not have it in our sample because the national statistical agency (INEGI) restricts data access to vetted researchers in a secure microdata lab.

[4]In 36 of the 41 countries we cover, the data come from the BPS. In Guatemala, Honduras, Nicaragua, El

of the countries in our sample are classified as low- or middle-income. At the low end we cover Malawi, Madagascar, Sierra Leone, and Tanzania. At the high end, we have Bulgaria, Turkey, Malaysia, Romania, and Poland.

Data collection in our 41 countries took place between April 2020 and January 2022. In 18 of them, the BPS collected follow-up survey waves that re-interviewed many of the participating firms, so we are able to track firm performance across waves. In the other 23 countries we only have data from a single wave (i.e., a single cross-section). Altogether, our dataset includes 65 country-wave combinations. See Table A3 in the appendix for the full list of countries and a timeline of when each survey wave took place. See Table A4 for information about the number of panel observations in countries with multiple waves.

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. The surveys therefore focus on businesses that operate primarily within the formal economy, but in many cases these registered businesses hire both formal and informal labor. The surveys ask about firm-wide sales and employment, so our data cover a broad picture of the business sector even where the informal economy is large.

In terms of coverage, we survey firms belonging to most manufacturing and services sectors, ranging in size from small (5 to 19 workers) to medium (19 to 99 workers) and large (100 or more workers). The BPS and ES did survey micro firms (with fewer than 5 workers), but they did not ask the key questions we use to measure expectations, uncertainty, and absolute forecast errors. Therefore, we exclude micro firms from our sample. We also exclude firms operating in social services sectors (education and health) due to differences in coverage across countries, and given the large role the government plays in those industries. Finally, we exclude firms where we are able to contact a manager, but they report the firm closed permanently by the time of the interview. Table A5 shows the coverage across size groups and sectors for each country in our sample.

### 2.2 Eliciting subjective probability distributions and measuring expectations and uncertainty

We obtain data on manager expectations and uncertainty from a module of the BPS and ES that elicits subjective probability distributions about own-firm sales at a six-month look-ahead horizon. Table 1 shows the English-language versions of the underlying survey questions. 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)

Salvador, and Mongolia, the surveys were follow-ups to an earlier Enterprise Survey (ES) and they used the same questionnaire as the global BPS.

and a probability for that outcome. Then we ask them to consider a more optimistic and a more pessimistic scenario, and a probability for each of those. For each complete response, therefore, we obtain subjective distributions with three support points and three corresponding probabilities.

Mathematically, each subjective distribution consists of a vector of support points $\{g_i\}_{i=1}^{3}$ and a vector of probabilities $\{p_i\}_{i=1}^{3}$ where $i$ indexes the three (pessimistic, central, and optimistic) scenarios. We express the respondent's estimate of six-months-ahead sales as an arc-change from the prior year.[5] We follow the literature on business dynamics in favoring arc-changes because they are symmetric around zero, they approximate log-changes, and have desirable aggregation properties. See Davis et al. (1998) for more details.

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

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

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

$$\text{Uncertainty} = \left[\sum_{i=1}^{3} p_i \left(g_i - \text{Expectation}\right)^2\right]^{\frac{1}{2}}. \tag{2}$$

We cannot compute these subjective moments unless the probability distribution provided by a respondent satisfies the following criteria: (1) The respondent must provide two or three separate support points for potential future sales; (2) the sum of the probabilities equals 100; and (3) the standard deviation of the distribution is strictly positive. Our analysis sample focuses on those survey responses where we can obtain distributions that comply with these criteria.

In some cases, we make small imputations to the probability vector provided by a respondent to obtain a distribution that we can use to measure expectations and uncertainty. First, we take distributions with three support points whose probabilities sum to more than 50 but less than 150, and we rescale the probabilities to sum to 100. Second, we take distributions with missing probabilities or whose probability vectors sum to less than 50 or more than 150 and impute the entire probability vector based on the sample average for the same country and wave. We would prefer not to have to make these imputations,

[5] Assuming the respondent's raw estimate as provided to the enumerator in scenario $i$, $h_i$ represents a proportional change (so $h = .01$ means a 1% increase), the arc-change is $g = {}^{2h}/_{(h+2)}$. To see why, note that if $h \in [-1, \infty)$ is a proportional change for variable $x$, then $h = (x' - x)/x$ where the prime indicates the future value of $x$. The arc-change, then, is $g \equiv (x' - x)/(0.5(x' + x)) = 2h/(h + 2)$.

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 (between 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 (between 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 (between 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 list of questions in the BPS.

but we are confident that cleaning the probability vectors in this way does not materially affect our measures of expectations and uncertainty. Indeed Altig et al. (2022) show, for a similar survey, that the vector of support points matters much more when measuring expectations and uncertainty than the vector of probabilities.

After completing the above imputations, we drop degenerate subjective distributions; namely, those implying zero standard deviation because the respondent assigns the same expected change in sales for each scenario or 100% of the probability mass to a single scenario. Such degenerate distributions amount to 15% of the raw sample. Ultimately, distributions where we rescale or impute the probability vector and end up with a suitable non-degenerate distribution account for 24.4% of the raw sample. Table A6 shows the number of subjective distributions in the raw data and the final sample, grouping country-waves by the calendar quarter when the last interview was completed.

Our raw data include almost 40,800 subjective distributions frome 31,219 unique managers. Almost 24,000 managers participated in the survey once, and a further 7,300 participated twice or more. After doing our imputations and dropping responses where we cannot measure uncertainty, we end up with 28,612 subjective distributions from 41 countries, amounting to 70% of the raw sample. This rate of success suggests it is feasible to elicit subjective probability distributions via surveys in a range of developing and emerging economies. Many of the survey waves in our data took place during times of significant turmoil associated with the COVID-19 pandemic. Improving survey implementation, question design, and institutionalization could likely increase the share of usable distributions well above that 70%. For comparison, Bloom et al. (2020b) obtain well-formed distributions from about 85% of US manufacturing plants responding to a mandatory Census survey.

The likelihood that a firm is unable to provide a well-formed subjective distribution in the BPS and ES declines with firm size wihin a given country, wave, and sector as Figure A2 shows in the appendix.[6] This pattern is consistent with the evidence in Bloom et al. (2020b) regarding US manufacturing plants, where productivity and firm size are associated with the ability to provide good forecasts and distributions. We conclude that eliciting subjective distributions is feasible in developing and emerging economies. By investing in implementation and infrastructure, we argue that central banks, statistical agencies, and other institutions around the world could replicate our survey efforts and

[6]We compute these likelihoods for 5 quintiles within country-wave-sector firm size distribution, and control for country and date fixed effects. We focus on these within relationships because the survey implementation varies modestly across countries and waves. We also control for the calendar quarter when a given survey took place to control for the evolution of the pandemic and the possibility that firms responding to a follow-up survey are more familiar with the format of the uncertainty module.

obtain measures of business expectations and uncertainty to inform research and policy.

### 2.3 Summary statistics about expectations and uncertainty

Panel (a) of Table 2 reports unweighted means and standard deviations for each of the three (optimistic, central, pessimistic) support points and their corresponding subjective probabilities. (Table A7 in the appendix shows the same statistics by calendar quarter.) Sales projections vary significantly across scenarios, and range from -45.2% for the pessimistic scenario to +15.5% for the optimistic scenario. 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). The other two (optimistic and pessimistic) support points have probabilities that average close to 30%. Overall, these statistics show one of the main benefits of letting respondents choose the support points and probabilities of their subjective distributions. By doing so, we are able to accommodate the vast heterogeneity in business prospects across firms, by letting managers themselves determine the location and the scale of the distribution of potential outcomes.

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

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

| | Scenario | Mean | Standard Deviation |
|---|---|---|---|
| Support point for future sales | Pessimistic | -0.45 | 0.56 |
| | Central | -0.08 | 0.42 |
| | Optimistic | 0.16 | 0.30 |
| Probability | Pessimistic | 27.5 | 15.9 |
| | Central | 38.8 | 16.7 |
| | Optimistic | 34.2 | 15.7 |

(b) **Expectations and Uncertainty Measures**

| | Mean | Standard Deviation |
|---|---|---|
| Expected six-months-ahead sales | -0.06 | 0.35 |
| Subjective uncertainty of six-months-ahead sales | 0.21 | 0.20 |

**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. 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.

To focus on estimates that are more relevant for the macro-economy, our analysis below uses weights that are proportional to economic activity (unless we note otherwise). That is, we weight each firm by 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.[7]

Panel (b) of Table 2 reports the employment-weighted mean and standard deviation of our measures of sales expectations and uncertainty in the full sample. (See Table A8 in the appendix for those statistics by calendar quarter.) Here, again, we see that our measures reflect vast heterogeneity across firms. While the average expectation calls for a 6% drop in sales over the next six months relative to the reference period, the standard deviation around that average is 35%. The average subjective uncertainty in the sample is 21%, with a standard deviation almost as large.

[7]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 the results.

## 3. Validating our measures of expectations and uncertainty

This section validates our measures of business expectations and uncertainty obtained from the BPS and ES surveys. In doing so, we replicate key results from earlier work surveying managers about future own-firm outcomes, namely Altig et al. (2022), Bloom et al. (2020a), and Bachmann et al. (2020).

We show that both measures informative about the future. In the subsample where we observe realized sales in the months after the survey, expectations predict future sales outcomes and uncertainty predicts absolute forecast errors. Moreover, our measures of uncertainty reflect shifts in the business environment. We also show how sales expectations and uncertainty correlate with future changes in employment at the firm.

### 3.1 Expectations predict future sales, and uncertainty predicts realized volatility

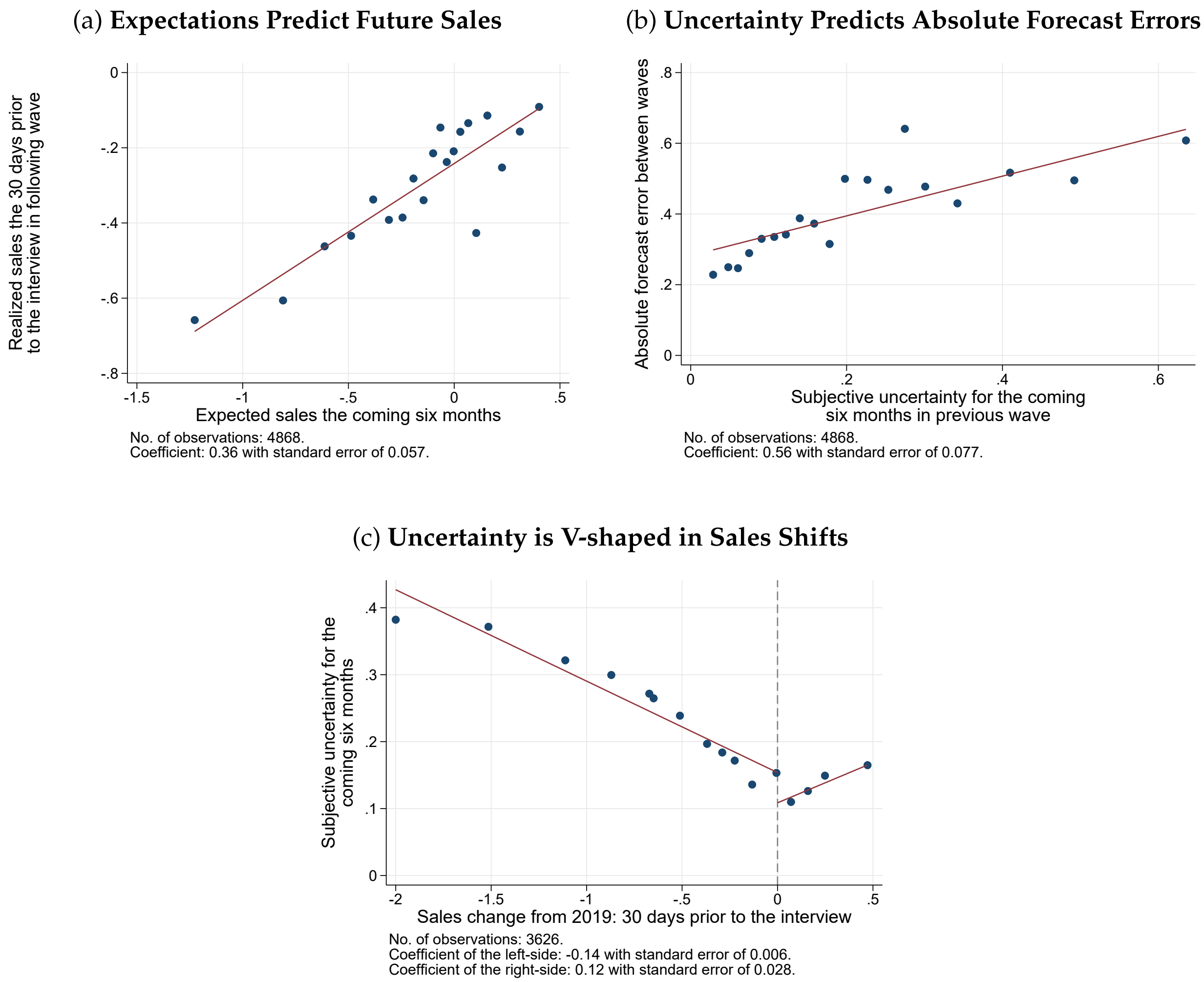
Our measures of business expectations and uncertainty contain information about future outcomes, which we show by exploiting the panel dimension of our survey data. The BPS and ES conducted follow-up survey waves in a number of countries, reaching many of the original participants and asking about realized sales outcomes.

In their first interview, managers provide expectations for own-firm sales in the next six months, expressed as a percent of sales in the prior year. Follow-up interviews in the ensuing months ask them about the firm's recent sales level, specifically in the 30 days prior to the interview, again expressed relative to the same reference period.[8] That means the question about realized sales level does not cover exactly the same time period as the original forecasting question. However, we believe it provides a reasonable approximation for realized sales in the months after the survey. In what follows, we ask whether expectations and uncertainty have any predictive power for those sales outcomes, noting that the timing mismatch could introduce some noise into these relationships.

There is a positive and significant relationship between a firm's sales expectations during the initial interview and the sales level it reports in the follow-up interview, as the binned scatter plot in panel (a) of Figure 2 shows. The slope is robust to whether we give firms equal weight or use our preferred employment weights. Qualitatively, this result is consistent with similar findings in Altig et al. (2022), Barrero (2022), and Bloom et al. (2020a), but the slope is flatter than in prior work. Our data are likely noisier than in that prior work, because of the timing mismatch between forecasts and realizations; because

[8] The exact wording of the questions that capture the realized change in sales 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.

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




**Notes:** Panel (a) shows a binned scatter plot of realized sales in the 30 days prior to the follow-up interview on the vertical-axis against sales expectations for the next six months as of the initial interview on the horizontal axis. Panel (b) shows a binned scatter plot of the absolute error between six-months-ahead sales expectations elicited in the initial wave and realized sales in the 30 days leading to the follow-up interview on the vertical-axis, against subjective uncertainty about six-months-ahead sales elicited in the initial wave on the horizontal-axis. Panel (c) shows a binned scatter plot of subjective uncertainty about six-months-ahead sales on the vertical axis against realized sales the 30 days prior to the initial interview on the horizontal axis. We winsorize subjective uncertainty at the 5th and 95th percentiles. Both realized sales and expected sales are expressed as arc-changes relative to the same period in the prior year. The sample for panel (c) includes businesses from all countries and waves. Panels (a) and (b) include only firm-level observations for which we have a follow-up interview in a subsequent wave. See Table A4 in the appendix for a list of countries where we have this sort of panel data. Estimates and plots in all panels are employment-weighted. The reported statistics below each figure correspond to the least squares regression in the underlying microdata and the corresponding robust standard error clustered by country-sector.

we collect data during the pandemic; and because we survey managers in developing and emerging economies who may be less sophisticated tha those in the US. Regardless, the positive and approximately linear conditional mean between expectations and realizations says that our expectations are informative signals about firms' future business outlook.

We also find a positive relationship between subjective uncertainty and realized sales volatility, measured by managers' absolute forecast errors. We compute those errors as the absolute value of the difference between the forecast (i.e., the expectation) and the reported actual sales in the follow-up interview.[9] Thus, managers who express higher uncertainty make forecasts that are less accurate, presumably because their firms get hit by more volatile shocks after the forecast. Panel (b) of Figure 2 shows the employment-weighted binned scatter plot of this relationship. As with expectations, this relationship is likely subject to measurement error in subjective uncertainty and compares forecast and realization periods that don't always match, so the slope coefficient is somewhat lower than in corresponding tests in Altig et al. (2022) and Barrero (2022).

### 3.2 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 an employment-weighted binned scatter plot of subjective uncertainty against realized sales in the 30 days prior to the interview. The plot is v-shaped. When managers report large (positive or negative) shifts in recent sales they express higher uncertainty about six-months-ahead sales. We partition the sample at zero along the horizontal axis and report the coefficients from independent regressions in each subsample. In both cases, we estimate a statistically and economically significant relationship between the size of the sales shift and uncertainty.

Figure A1 in the appendix reports three additional tests that link uncertainty to a shifting or volatile business environment. Uncertainty increases with the absolute value of the managers' sales forecast. Managers express higher uncertainty in follow-up interviews after making large absolute forecast errors. Finally, managers express higher uncertainty in follow-up interviews when their six-months-ahead sales forecast in that second interview differs in absolute value from the one in the first interview; especially when the second forecast is lower. All three of these results suggest managers are more uncertain when the experience big changes in their firm's outlook, whether in the recent past, or looking toward the future.

These results replicate similar findings from surveys of managers in Germany (see

[9]As with the future sales outcomes in the expected distribution, we express the realized sales level as the arc-change from the reference period.

Bachmann et al., 2020) and the United States (see Altig et al., 2022 and Bloom et al., 2020a). They serve as confirmation that our measures of subjective uncertainty reflect instability in the firm's environment.

### 3.3 Expectations and uncertainty correlate with employment changes

As a final test of the validity of out data, we regress changes in the firm's employment during the 30 days prior to the survey interview on expectations and uncertainty about six-months-ahead sales. Table 3 shows the results. In the raw cross section in column 1, managers who forecast high sales in the next six months report higher recent employment growth. Those who report high uncertainty instead report lower employment growth, but the statistical significance of that estimate is weak. We find a similar pattern in column 2, which adds country-by-sector fixed effects. Column 3 adds quarter fixed effects to control for differences over time. There, the relationship between expectations and employment weakens, but but the one between uncertainty and employment is stable.

The results in Table 3 link firm decisions to expectations and uncertainty, at least in the cross section. Stronger tests would use within-firm variation to see if the same firm's employment tends to change with fluctuations in expectations and uncertainty, as Barrero (2022) and Ma et al. (2020) do. We are unable to run those tests because we only have a short panel. That said, we are reassured that the signs seem to go in the right direction, under the hypothesis that better sales prospects push managers to hire more workers, and uncertainty tends to dissuade them.

Table 3: **Expectations and Uncertainty Correlate with Employment Changes in the Cross Section**

| | (1) | (2) | (3) |
|---|---|---|---|
| | **Change in employment last 30 days** | | |
| Expected change in sales | $0.037^{***}$ | $0.027^{***}$ | $0.013^{+}$ |
| | (0.009) | (0.007) | (0.008) |
| Subjective uncertainty | $-0.013$ | $-0.020^{+}$ | $-0.020^{+}$ |
| | (0.012) | (0.013) | (0.013) |
| Country x Sector FE | No | Yes | Yes |
| Quarter FE | No | No | Yes |
| Observations | 19543 | 19542 | 18590 |
| $R^2$ | 0.010 | 0.078 | 0.100 |
| Within $R^2$ | | 0.005 | 0.002 |
| No. of clusters | 185 | 184 | 179 |

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

## 4. Two new facts about business uncertainty across countries

Having validated our data on expectations, uncertainty, and absolute forecast errors, we establish the two new facts about uncertainty and volatility across countries. These are the two facts shown in Figure 1.

1. Uncertainty and volatility (the latter measured using absolute forecast errrors) both decline with GDP per capita, as Figure 1a shows.

2. Managers underestimate sales volatility; namely they are *overprecise*. In every country where we can compute average uncertainty and absolute forecast errors, the latter are larger, as we can see in Figure 1b. Moreover, we argue the degree of overprecision is higher in rich, low-volatility countries.

### 4.1 Uncertainty and volatility decline with GDP per capita

Figure 1a computes employment-weighted average uncertainty and volatility (i.e., absolute forecast errors) for every country in our sample and plots them against 2019 PPP-adjusted GDP per capita (expressed in 2019 US dollars). In both cases we can see a negative relationship, and confirm it by plotting the linear fit from the two regressions estimated on the cross-country data. We the data points for Sierra Leone from this chart, because our estimate of the volatility (absolute forecast error) there is far larger than in other countries and we want to avoid that outlier influencing our results.

To test whether the pattern in Figure 1a extends to high-income countries, we also add data points (in red and orange) from the US Survey of Business Uncertainty (SBU). The SBU is run monthly out of the Atlanta Fed (see Altig et al., 2022), and collects distributions about four-quarters-ahead sales growth. We obtain the pre-pandemic USA point by pooling data from from the October 2014 to May 2019 waves of the SBU and computing the employment-weighted average uncertainty and absolute forecast error. The unlabeled USA point uses data from June 2020 to March 2022, spanning the sample period of our World Bank survey data. Despite modest differences between the Atlanta Fed and World Bank data, the USA data points in Figure 1a line up with the cross country evidence and show low levels of uncertainty and volatility at high GDP per capita, before and after the pandemic.

Figure 3a takes a more granular approach. It computes employment-weighted average uncertainty in each country-wave and still shows a negative relationship when plotted against GDP per capita. Several months elapse between survey waves in most countries, so allowing for wave-specific uncertainty estimates provides added flexibility and suggests the pattern in Figure 1a does not simply arise because we interview poor countries during severe pandemic lockdowns, and richer ones in better times.

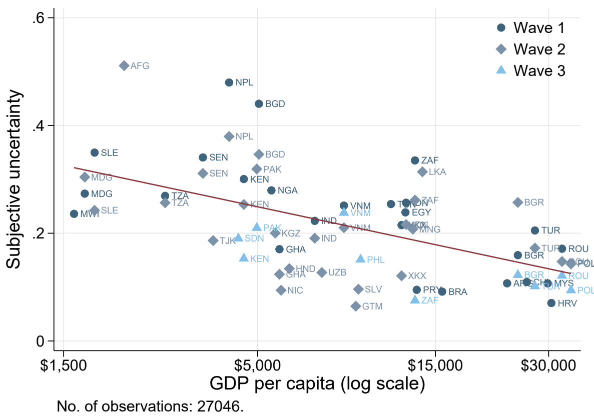
Businesses in high-, middle-, and low-income countries differ systematically. If those differences are correlated correlated with uncertainty and volatility, they could explain away the negative relationship between uncertainty and GDP per capita. For example, firms are larger in higher-income countries (see, e.g., Bento and Restuccia, 2017, and Poschke, 2014), and larger firms are also less volatile (see, e.g., Davis et al., 2006) because they aggregate across more clients and lines of business with imperfectly correlated demand shocks. The distribution of economic activity across industry sectors also differs across countries. If lower-income countries have a higher share of, say, retail businesses that were subject to especially widespread disruption due to the pandemic, that could also drive the pattern in Figure 3a. Indeed, Koren and Tenreyro (2007) link macro volatility in lower-income countries to their sector compositions.

To address those concerns, figure 3b shows a binned scatter plot of uncertainty against GDP per capita that controls for firm size (i.e., log(Employment)), sector fixed effects, and date fixed effects to control for survey timing. Adding those controls does little to change the level or slope of the relationship.

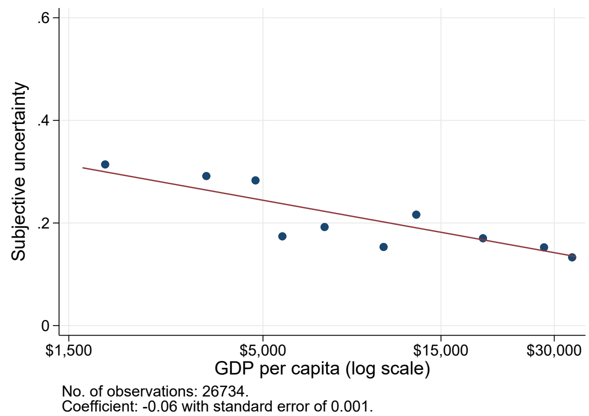
Figure 3: **Uncertainty and Volatility Decline with GDP per Capita**

## Uncertainty vs. GDP per Capita

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

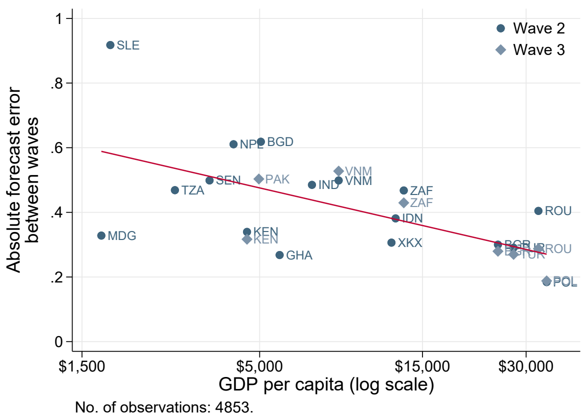



(b) **Controls for Firm Size, Sector, and Quarter**

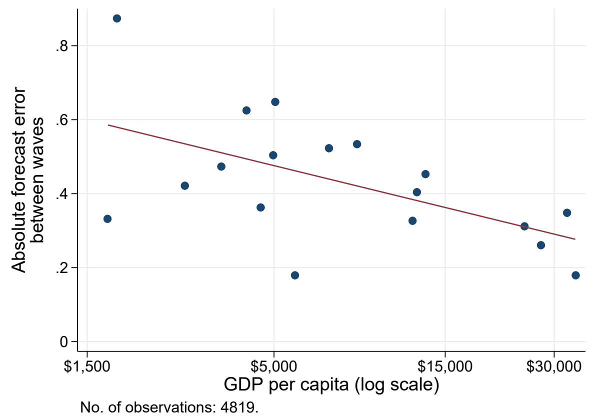



## Volatility (Absolute Forecast Errors) vs. GDP per Capita

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

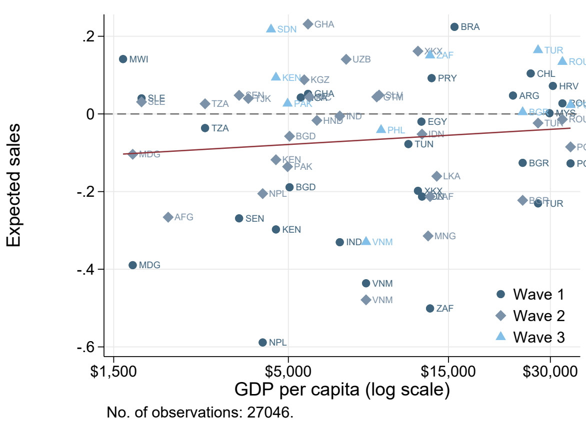



(d) **Controls for Firm Size, Sector, and Quarter**

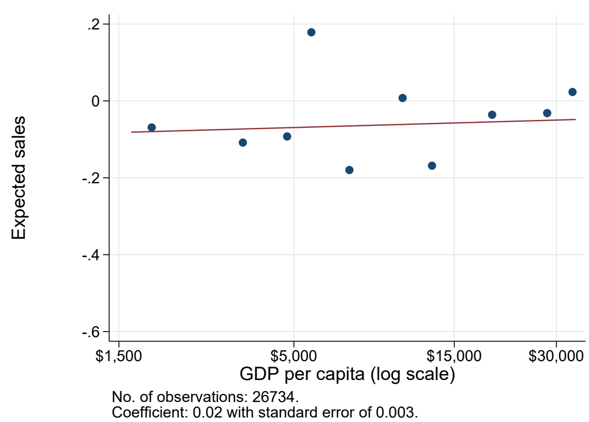



## Expected Sales vs. GDP per Capita

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




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




**Notes:** The vertical axis in each panel shows employment-weighted averages across firms in each country-wave (left panels) and in the pooled data (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. In all cases, 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.

Table 4 conducts further tests to show that managers in poor countries are systematically more uncertain than managers in rich countries. In column 1, we regress firm-level uncertainty against GDP per capita, controling for log(Employment), sector and quarter fixed effects, and for an index of mobility around transit stations. The latter control is meant to capture lockdown stringency around the time of the survey, since pandemic-related business closures could generate much uncertainty for managers. We obtain a large and significant coefficient of -0.06 on GDP per capita.

Column 2 adds a control that measures the firm's absolute change in sales in the 30 days prior to the interview. As we saw in panel (c) of Figure 2 recent shifts in sales are a strong predictor of firm-level uncertainty. The coefficient on GDP per capita drops by about one third, but it remains negative and significant. As we add controls for the variability of countries' GDP in the 10 years after the Global Financial Crisis, for sales dispersion in the firm's country-wave-sector, and exchange rate volatility, the coefficient remains stable between .042 and .047 and highly significant. It drops slightly in columns 6 and 7 when we restrict the sample to the subset of countries where we can classify the country's exchange rate regime.[10] However, adding or removing exchange-rate-regime fixed effects matters little for the coefficient, as we see by comparing columns 6 and 7.

Altogether, Table 4 suggests there is a robust negative relationship between uncertainty and economic development as measured by GDP per capita, even after controlling for a range of micro- and macroeconomic variables that predict uncertainty and GDP per capita. This result echoes that by Koren and Tenreyro (2007) that country-specific aggregate shocks are more volatile in lower-income countries. But the robustness of our result suggests we uncover a separate phenomenon. Our preferred estimate of the GDP-uncertainty slope from column 5 implies that a firm operating in a country with GDP per capita of $30,000 perceives uncertainty that is lower by .084 (= 0.047(log(30,000) - log(5000)) ) compared with a firm in a country with $5,000 GDP per capita. That is about 40% as large as the mean subjective uncertainty of 0.21.

We cannot establish a causal link between uncertainty and GDP per capita. One hypothesis for why managers are more uncertain in poor countries says that weak institutions keep countries poor and also make business more uncertain. We are sympathetic to that hypothesis, so Table A1 in the appendix tests whether controlling for perceptions of corruption, trust, or individualism explain away the patterns between GDP per capita and uncertainty. Those variables are only available for a subset of the countries in our data, and

[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

when we include them in our regressions we continue to estimate a negative relationship between GDP per capita and uncertainty.

Our data also suggest that managers in poor countries have good reasons to be more uncertain than those in richer ones. Figure 3c plots firm volatility, measured by employment-weighted average absolute forecast errors, in each country-wave where we have panel data against GDP per capita. Here, again, there is a negative relationship. As before, Figure 3d shows this negative relationship is hard to explain away with cross-country differences in firm size, sector, or the evolution of the pandemic.

Table 5 conducts further tests to show that firm volatility declines with GDP per capita, even when we control for a range of micro and macro predictors of volatility. The slope between volatility and GDP per capita drops when we add macro controls in moving from columns 1 to 2, and 5 to 6. But the resulting coefficients after adding those controls are significant and comparable to the ones from Table 4. Columns 3, 4, and 6 show that uncertainty is a robust predictor of absolute forecast errors, replicating the finding from panel (b) of Figure 2. In fact, column 6 shows that uncertainty and GDP per capita have independent predictive power for absolute forecast errors at the firm level. GDP per capita, therefore, predicts higher volatility even when we control for managers' (absence of) information about future business prospects.

The patterns in Figures 3a to 3d are consistent with the argument in Asker et al. (2014) that firm-level productivity is more variable in lower-income countries, and there is also greater dispersion in the marginal product of inputs. But our results say more. We show managers perceive more uncertainty and experience more volatility in poor countries even conditional on the private information they have about their own firm. Thus, our results say that volatile measures of productivity and high dispersion in marginal products in poor countries are probably not due solely to higher measurement error (e.g., see Bils, Klenow, and Ruane, 2021).

There is little evidence, by contrast, that business expectations vary systematically with economic development. Figure 3e plots employment-weighted average expected sales in each country wave of our survey data against GDP per capita. At a given level of GDP per capita there wide dispersion in expected future sales. The figure provides little evidence of an upward- or downward-sloping relationship. The binned scatter plot in 3f, which controls for firm size, sector, and calendar quarter, traces an essentially horizontal relationship between expectations and GDP per capita. Table A2 in the appendix regresses expectations on GDP per capita and a host of controls, also failing to find a relationship.

Table 4: **Uncertainty Declines with GDP per Capita**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | **Subjective Uncertainty** | | | |
| GDP per capita (log) | -0.061*** | -0.048*** | -0.046*** | -0.043*** | -0.047*** | -0.038*** | -0.034*** |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) | (0.005) |
| Absolute change in sales | | 0.118*** | 0.119*** | 0.113*** | 0.111*** | 0.110*** | 0.109*** |
| | | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| GDP SD 09-19 / Mean | | | 0.504** | 0.498** | 0.671*** | 1.163*** | 1.269*** |
| | | | (0.243) | (0.237) | (0.230) | (0.198) | (0.184) |
| SD (arc) change in sales by country-wave-sector | | | | 0.073** | 0.076** | 0.108*** | 0.084** |
| | | | | (0.030) | (0.030) | (0.031) | (0.034) |
| Exchange rate volatility last 30 days | | | | | 0.806** | 0.751** | 1.521*** |
| | | | | | (0.363) | (0.349) | (0.453) |
| Exchange rate regime dummies | No | No | No | No | No | No | Yes |
| Mobility and size | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector and quarter dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26,734 | 25,892 | 25,892 | 25,892 | 22,986 | 20,854 | 20,854 |
| Within $R^2$ | 0.088 | 0.167 | 0.171 | 0.173 | 0.194 | 0.200 | 0.208 |
| No. of clusters | 195 | 195 | 195 | 195 | 151 | 124 | 124 |

**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 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) | $-0.104^{***}$ | $-0.049^{**}$ | | | $-0.087^{***}$ | $-0.041^{*}$ |
| | (0.027) | (0.021) | | | (0.027) | (0.022) |
| Uncertainty in previous wave | | | $0.363^{***}$ | $0.236^{***}$ | $0.271^{***}$ | $0.223^{***}$ |
| | | | (0.081) | (0.080) | (0.078) | (0.080) |
| GDP SD 09-19 / Mean | | $-1.742$ | | $-1.240$ | | $-1.503$ |
| | | (1.383) | | (1.410) | | (1.359) |
| SD (arc) change in sales by country-wave-sector | | $0.399^{***}$ | | $0.447^{***}$ | | $0.367^{***}$ |
| | | (0.109) | | (0.105) | | (0.108) |
| Exchange rate volatility last 30 days | | $-2.960^{**}$ | | $-2.782^{**}$ | | $-3.196^{**}$ |
| | | (1.314) | | (1.369) | | (1.282) |
| Exchange rate regime dummies | No | Yes | No | Yes | No | Yes |
| Size | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector and quarter dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4659 | 4622 | 4659 | 4622 | 4659 | 4622 |
| Within $R^2$ | 0.055 | 0.091 | 0.041 | 0.099 | 0.073 | 0.103 |
| No. of clusters | 88 | 81 | 88 | 81 | 88 | 81 |

**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. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

### 4.2 Managers are *overprecise* in all countries in our data, and more so in rich countries

Our second new fact in this paper says that business uncertainty deviates systematically from measured volatility in all countries where we can track firm outcomes. Namely, managers are *overprecise*. Measures of uncertainty derived from their subjective distributions underestimate the magnitude of forecast errors, as in Ben-David et al. (2013), Boutros et al. (2020) and Barrero (2022).

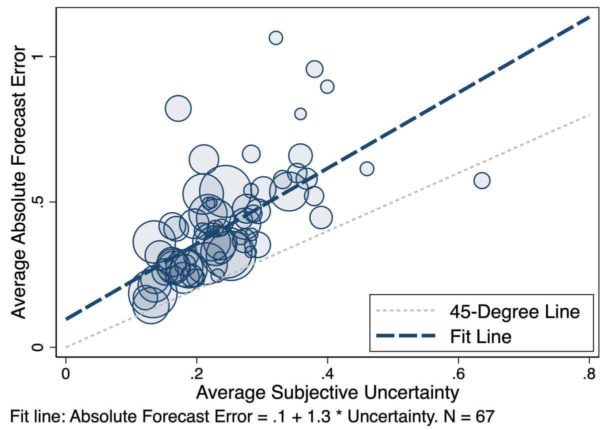
Figure 1b plots employment-weighted average volatility (i.e., average absolute forecast errors) against average uncertainty by country and the linear OLS fit between those two variables. Again, we drop the data point for Sierra Leone because our estimate of volatility there is implausibly large, and bring in data points for the US from the Atlanta Fed Survey of Business Uncertainty. In all of the countries plotted volatility exceeds uncertainty, as we can see because all points are above the 45-degree line. If managers had rational expectations, and there were no large common shocks, we would instead expect average uncertainty to be about as large as the average absolute forecast error in each country.

We find a similar pattern when we repeat this exercise at the country-sector level in 4a . We compute average uncertainty and volatility across 67 country-sectors where we have at least 20 forecast error observations, and plot them against each other. As with the cross-country evidence, we find a positive relationship between uncertainty and volatility. And in 66 out of 67 country-sectors, we estimate realized volatility (absolute forecast errors) that exceeds subjective uncertainty. In fact, the the firm level binned scatter plot in panel (b) of Figure Figure 2 also shows a positive relationship that lies mostly above the 45-degree line, providing more evidence of overprecision in our broad sample.

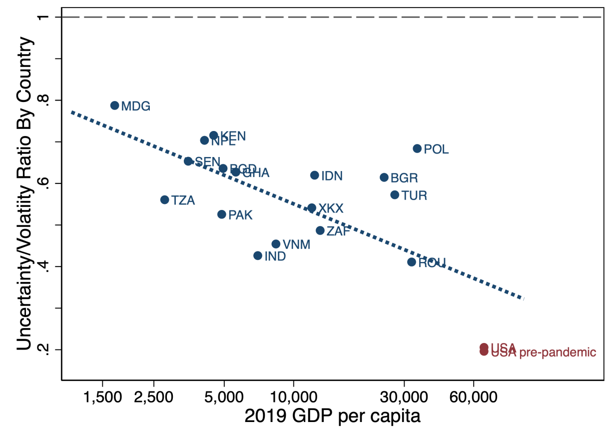
In both Figures 1a and 1b there seems to a constant gap between uncertainty absolute forecast errors as we move along the horizontal axis. Figure 4a is noisier, but a linear regression estimates a constant of 0.1 and a coefficient of 1.3, very similar to the regression estimates from Figure 1b. Managers seem to underestimate volatility by a constant (additive) amount across levels of uncertainty and GDP per capita. The corollary to that observation is that managers in rich countries, where volatility is lower, underestimate it by a higher *percentage*. To confirm this intuition, Figure 4b takes our country-level statistics and plots the ratio of uncertainty to absolute forecast errors against GDP per capita. We obtain a downward sloping relationship uniformly below 1, which indicates more severe overprecision as we move to the right. Poor countries with 2019 PPP GDP per capita under $2,500 have ratios of 0.7 to 0.8, so managers underestimate volatility by 20% to 30%. For high-income countries, with GDP per capita over $30,000, the underestimate amounts to 60% or more.

Figure 4: **Managers are Overprecise in Most Country-Sectors, and Especially in Rich Countries**

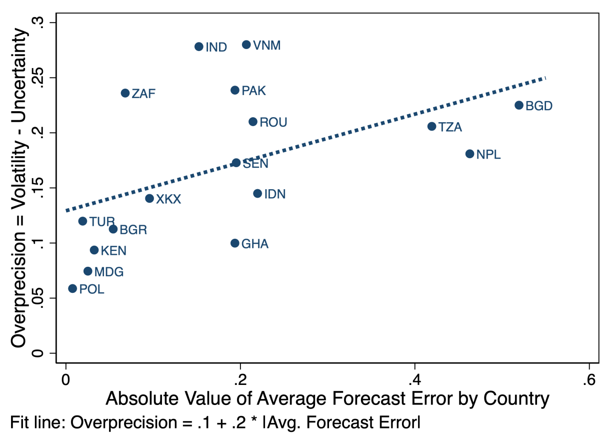
(a) **Volatility vs. Uncertainty by Country-Sector**



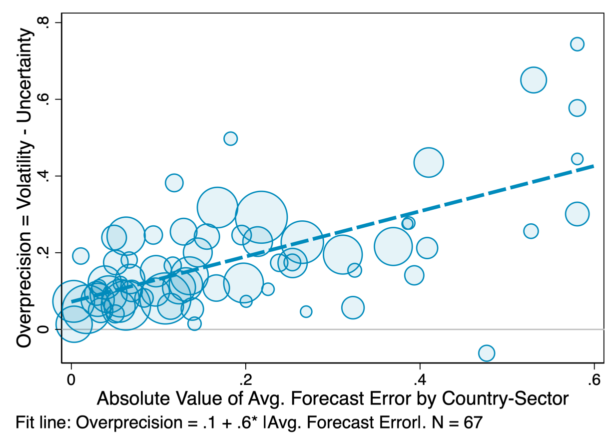

(b) **Rich-Country Managers are More Overprecise**




(c) **Overprecision vs. Common Shock by Country**




(d) **Overprecision vs. Common Shock by Country-Sector**




**Notes:** The vertical axis in each panel shows, for each country, the employment-weighted average of the difference between absolute forecast errors and ex-ante subjective uncertainty. Businesses 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.The right panel has the employment-weighted average (non-absolute) forecast error across firms in a given country.

That managers are more overprecise in rich countries raises questions about the nature of corporate governance and CEO selection. 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 entrepreneurs in rich countries is small and skewed towards people who have good ideas and underestimate risk. On the other hand, 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), especially if rich-country firms have more demand for those traits (see, e.g. Eisfeldt and Kuhnen, 2013).

Our tests for overprecision all rely on the absence of large common shocks that raise our measure of volatility in a given country or country-sector. Such shocks could lead us to conclude managers are overprecise, when the relevant test is polluted by small-sample issues in the time dimension. Although our World Bank data was collected during the turbulent period spanning 2020 to early 2022, we are skeptical that our tests for overprecision are being driven by common shocks. To start, Figures 4c and 4d plot the gap between uncertainty and absolute forecast errors against the average common shock in each country or country-sector. Namely, they put the absolute value of the average forecast error on the horizontal axis. In both cases, the plot shows slopes that are shallower than 1. More importantly, we estimate positive gaps of about 0.1 between uncertainty and volatility even for countries and country-sectors with near-zero common shocks. Those gaps are consistent with our baseline measure of overprecision.

There is also ample evidence of managerial overprecision that predates 2020. In Figure 1, absolute forecast errors exceed uncertainty in pre-pandemic US data, a fact originally documented by Barrero (2022). Interested readers may want to refer to the discussion in that paper (and its online appendix) that argues overprecision is not driven by factors such as overextrapolation bias or the discrete nature of the subjective distributions collected in our surveys. 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. In sum, this pre-pandemic evidence together with Figures 4c and 4d, make us skeptical that common shocks are the primary driver of overprecision in our cross-country data.

## 5. 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 respond to both uncertainty and volatility. Specifically, we focus on dynamic investment and entry-and-exit decisions for which ex-ante uncertainty and ex-post shocks matter.

Our model focuses on the economy of a single country, which we assume takes the world interest rate $r$ as given and focus on equilibria where the country's internal labor market clears. Without loss of generality, we normalize aggregate labor supply to 1.

To keep notation light, we typically 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 (′).

### 5.1 Production and variable profits

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

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

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

Each period, managers hire labor to maximize static variable profits, taking the equilibrium wage $w$ as given. After optimizing, variable profits can be written as a function of capital and two new idiosyncratic and aggregate shifters $z$ and $A$ that depend only on parameters of the physical production function and the equilibrium wage:

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

where $\alpha \equiv \frac{\hat{\alpha}\nu}{1-(1-\hat{\alpha})\nu} < 1$.[11] The the firm's labor choice is also proportional to variable profits:

$$\begin{aligned} n^*(A,z,k,w) &\equiv \arg\max_{n} \hat{A}\hat{z}\left(k^{\hat{\alpha}} n^{1-\hat{\alpha}}\right)^{\nu} - wn \\ &= \frac{Azk^{\alpha}}{w} \frac{[(1-\tilde{\alpha})\nu]}{(1-\tilde{\alpha})\nu]^{(1-\tilde{\alpha})\nu} - (1-\tilde{\alpha})\nu}. \end{aligned}$$

Total profits (before considering investment or external financing) are variable profits less a fixed cost of operation: $Azk^{\alpha} - f$. This fixed cost will induce some managers to prefer to liquidate the firm and give up future cash flows, rather than continue operating unprofitably. Due to the Cobb-Douglas functional form of the revenue function, variable profits are proportional to revenue.

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

### 5.2 Shocks to firm profitability and how managers forecast future shocks

Firms are subject to idiosyncratic profitability risk that follows an AR(1) process:

$$\log(z') = \rho \log(z) + \sigma\varepsilon'$$

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

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

Managers underestimate are overprecise (they underestimate the conditional volatility) if and only if $\tilde{\sigma} < \sigma$. While our specification for the beliefs process is reduced form, it is possible to derive it from a setup where managers receive a signal of future profitability not available to the econometrician, but managers overestimate the precision of that signal. For example, see, Alti and Tetlock (2014), who model managerial overprecision and use it to explain asset pricing anomalies.

### 5.3 Incumbent managers' investment and exit 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. In our baseline specification, we focus on the case where investment is partially irreversible. 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, and we plan to test how robust our quantitative results are to changing those assumptions.

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 finance some investment with outside capital and incur a proportional cost of $\psi$. That makes external financing costly and is another friction to investment. In our baseline specification we set $\psi = \infty$ to shut down all external financing for existing firms, but we relax that assumption in our robustness tests.

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

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

In words, the manager's valuation of the firm $\tilde{V}(z,k)$ is the maximum of 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 profits plus the liquidation value of invested capital. When the manager chooses to continue in the market, they choose next period capital $k'$ 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 $z'$.

### 5.4 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 stationary distribution, 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 in that case must choose how much initial capital $k_1$ to inject into the business before starting operations in the next period. That initial capital injection costs the manager $(1+\psi^e)$ times the amount invested, so $\psi^e$ represents initial financing and startup costs.

Potential entrants' problem is therefore:

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

where again the manager forecasts $z_1$ using their subjective stochastic process, so the subjective expectation assumes $\log z_1 = \rho \log z_0 + \tilde{\sigma}\varepsilon_1$ with $\varepsilon_1 \sim \mathcal{N}(0,1)$ independently across firms.

### 5.5 Stationary equilibrium and GDP

A stationary equilibrium is characterized by a set of manager valuations for their business $\tilde{V}(z,k)$ 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 $\int_{z,k} n^*(A,z,k,w)\mathrm{d}z\mathrm{d}k = 1$.
- The mass of entrants $M$ equalizes entry and exit: $\int_{z,k} \mathbf{1}(\tilde{V}^l(z,k) \geq \tilde{V}^c(z,k)) \cdot \phi(z,k)\mathrm{d}z\mathrm{d}k = M\int_{z_0} \mathbf{1}(\tilde{V}^e(z_0) > 0) \cdot \phi_0(z_0)\mathrm{d}z_0$.

Equilibrium GDP is the sum of output less the fixed costs of operation across all firms in the country. 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, GDP in the country is given by:

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

### 5.6 Our cross country facts about business uncertainty and volatility in the model

Our goal in building the model is to create a laboratory where we can explore how perceived uncertainty and actual volatility matter for investment, entry, and exit decisions that are characterized by real options. The structure of the model is engineered to capture our key facts about cross-country uncertainty.

Suppose we were to simulate a large number of countries, indexed by $j$, that differ in terms of the parameters governing TFP, uncertainty, and volatility. Our empirical results say that the joint distribution of parameters should satisfy the following:

1. Uncertainty and volatility decline with GDP per capita, so $Corr(A_j, \sigma_j) < 0$ and $Corr(A_j, \tilde{\sigma}_j) < 0$;

2. Managers underestimate volatility in all countries, and proportionally more so in rich countries, so $\tilde{\sigma}_j < \sigma_j \forall j$ and $Corr(A_j, \tilde{\sigma}_j/\sigma_j) < 0$.

In the following section, we choose the key parameters of our model to match the empirical evidence about perceived uncertainty, realized volatility, and GDP per capita.

## 6. Development accounting when uncertainty and volatility differ across countries

We use a series of development accounting exercises (see, e.g., Caselli, 2005, and Hsieh and Klenow, 2010) to study the implications of uncertainty and volatility for investment and entrepreneurial dynamics. The goal of these exercises is to ask:

- How do manager perceptions of uncertainty in high- and low-volatility environments change the incentives to invest, to start, and keep operating businesses?
- How much do those differences in uncertainty and volatility matter?

Motivated by the cross-country patterns in uncertainty and volatility from Section 4, we frame our analysis in terms of (well-known) cross-country gaps in GDP per capita and aggregate TFP. Namely, we proceed by asking, how much do uncertainty and volatility matter when we try to account for why some countries are rich and others are poor?

### 6.1 Setup and empirical targets

Our development accounting exercises consider three hypothetical countries: (1) a high-income country with GDP per capita equal to that of the US (about \$66,000 in 2019 at purchasing power parity); (2) an upper-middle income country with GDP per capita about half as the US, which is near the top of our sample from the World Bank survey data; and (3) a low-income country with GDP per capita of about \$5,000, or about 7% as high as the US. As a shorthand, we refer to these three hypothetical countries as the "US", "Poland", and "Kenya". Our goal is to find a set of parameters for each country that can match our facts about cross-country uncertainty and volatility and also the gaps between the three countries' GDP per capita.

For this exercise, we fix a set of parameters for technology, adjustment, and financing costs that we hold constant across countries. We set the length of a time period in the model to be a half-year in accordance with the look-ahead horizon of the World Bank

BPS and ES survey data (see Section 2 ). Table 6 shows the fixed parameters, taking their values primarily from prior literature, and often based on economic benchmarks that are easy to interpret. Decreasing returns in the variable profit function come from a capital share of 0.35 in physical output, and returns-to-scale in revenue of 0.80, which is comparable to a Dixit-Stiglitz framework with 25% markups. The autocorrelation of firm shocks $\log(z)$ is consistent with the value of 0.95 across quarters used by Khan and Thomas (2008). The degree of investment irreversibility, with resale losses of 30%, is somewhat lower than the corresponding estimate in Bloom (2009). In our baseline specification we don't allow incumbents to finance investments externally ($\psi = \infty$), which is a reasonable approximation for small and medium businesses in emerging and developing economies. We also impose a 5% cost on entrants' initial capital injection ($\psi^e = 0.05$). In Section 6.3 below we test the sensitivity and robustness of our quantitative results to our assumptions about these parameters.

Table 6: **Accounting Exercise: Fixed Parameters**

| **Parameter** | **Description** | **Value** | **Notes** |
|---|---|---|---|
| $\hat{\alpha}$ | Capital share, output | 0.35 | Conventional |
| $\nu$ | Decreasing returns, output | 0.80 | 20% markups |
| $\alpha$ | Decreasing returns, var. profit | 0.58 | $\tilde{\alpha}\nu/(1-(1-\tilde{\alpha})\nu)$ |
| $\rho$ | $Corr(\log(z'), \log(z))$ | 0.90 | .95/qtr., cf. Khan and Thomas (2008) |
| $\delta$ | Depreciation | 0.05 | 10% annual |
| $\gamma$ | Capital resale loss | 0.30 | 30% resale loss |
| $\psi$ | Cost of external fin., incumbent | $\infty$ | No external financing, incumbents |
| $\psi^e$ | 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.

Then we pick four parameters in each country to match four data moments shown in Table 7. We target cross-country differences in GDP per capita – since that is what we want to account for in this exercise. We also target employment-weighted average subjective uncertainty and absolute forecast errors. Finally, we target a common exit rate of 0.05 (i.e., 10% per year) across all countries to discipline entrepreneurial dynamics in the model. Kochen (2022) estimates exit rates of that magnitude across several high- and middle-income countries, and Hsieh and Klenow (2014) also find similar exit rates across the US, India, and Mexico.

We compute our target moments for realized volatility (i.e., of average absolute forecast errors) and uncertainty using the empirical relationships in Figure 1a. Specifically, we regress country averages of absolute forecast errors and uncertainty on log(2019 PPP GDP per capita) and evaluate the linear fit at log(66,000), log(33,000) and log(5,000) to obtain target values for the "US," "Poland," and "Kenya." We specifically avoid using point estimates for the US, Poland, and Kenya computed from the survey data to focus on the predictable variation of uncertainty and volatility with GDP per capita, and to filter out idiosyncratic noise in those estimates. We assume our empirical measures of uncertainty and volatility reflect solely firm-specific risk, because in most settings that sort of risk is vastly larger than aggregate risk.

Table 7: **Full Accounting Exercise: Targets and Relevant Parameters**

| **Country** | **Relative GDP per capita** | **Uncertainty** | **Abs. Forecast Errors** | **Exit Rate** |
|---|---|---|---|---|
| "US" | 1.00 | .06 | .22 | .05 |
| "Poland" | .50 | .11 | .28 | .05 |
| "Kenya" | .07 | .23 | .44 | .05 |
| **Key Parameter** | $\hat{A}$ TFP shifter | $\tilde{\sigma}$ Subj. vol. | $\sigma$ Obj. vol. | $f$ Fixed cost |

**Notes:** This table shows the moments that we target in our development accounting exercise. We regress employment-weighted average uncertainty and volatility (average forecast errors) by country on log(2019 PPP GDP per capita). Then, we obtain the target uncertainty and volatility moments by evaluating the regression line at log($66,000) ("US"), log($33,000) ("Poland"), and log($5,000) ("Kenya"). We target an exit rate of 10% per year based on the long-run average for the US, Mexico, and several European Countries (e.g., Kochen, 2022). Note that GDP and GDP per Capita are equal in our model economies because we normalize aggregate labor supply (and thus the size of each country) to 1. See Section 5.

For each hypothetical country we simulate the vector of moments as a function of the four parameters that appear at the bottom of the table.[12] We then find a combination of those four parameters that minimize 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 mapping where we can fit the data moments very closely. In fact, there is an intuitive mapping from the four parameters to the moments:

- The country-wide TPF shifter $\hat{A}$ governs relative GDP per capita because $\hat{A}$ scales the overall productivity of firms in each country.

[12] We compute our simulated moments as similarly to the empirical moments as possible. For example, the survey asks managers to report future outcomes for the firm's sales relative to the prior year. Our empirical measures of expectations and uncertainty express those future outcomes as arc-changes relative to the same period in the prior year, and then compute the expectation and standard deviation using the probabilities provided by the manager. In the model, we also express potential changes in future sales as arc-changes relative to one year earlier, and then compute the expectation and standard deviation. Our country-level measures of uncertainty and volatility are employment-weighted averages, so we also weight firms by their employment $n^*(\cdot)$ when computing those moments in the model.

- The volatility of the subjective distribution $\tilde{\sigma}$ governs the level of average uncertainty by country.
- The volatility of the true shock process $\sigma$ governs average absolute forecast errors.
- The fixed cost of operation $f$ governs the exit rate.

Of course, all parameters have the capacity to change the moments generated by the model. But comparative static exercises confirm our intuitive mapping, conditional on the parameters we fix in Table 6.

### 6.2 Uncertainty, volatility, and aggregate TFP

We describe our quantitative analysis as an accounting exercise because we designed the model to match the vector of target moments nearly perfectly. The main object of interest is what set of parameters – in particular what level of the TFP shifter $\hat{A}$ – we need to match cross-country differences in GDP per capita. See Caselli (2005) and Hsieh and Klenow (2010) for more background of this sort of development accounting exercises.

To study how (and how much) differences in uncertainty and volatility matter, we run three versions of our accounting exercise. In the full exercise, we fit all four empirical moments from Table 7 with the four parameters. Then we see how the results differ when we ignore the two new facts about cross-country uncertainty and volatility from 4. First, we assume managers are not overprecise, so $\tilde{\sigma} = \sigma$, ignoring the evidence about subjective uncertainty across countries and focusing solely on differences in volatility (absolute forecast errors). In a second case, we continue to assume managers are not overprecise, so $\tilde{\sigma} = \sigma$, and set volatility equal at the "US" level across all three countries.

Table 8 reports the parameters that come out of the three versions of the accounting exercise. For aggregate TFP, we normalize "US" TFP to 1 and report the shifter of the revenue production fuction $\hat{A}$, which is closer to our object of interest than the shifter of the variable profit function $A$. (Recall from Section 5 that there is a one-to-one mapping from $\hat{A}$ to $A$ that depends only on the country's equilibrium wage $w$ and parameters of the revenue production function.) Table 8a reports, in addition to the parameters, the degree of overprecision implied by the full accounting exercise, expressed as a ratio between the subjective and objective volatilities. As we reasoned from the empirical results, overprecision is more severe in higher-income countries like the "US" and "Poland." Their managers believe the volatility of profitability is just 16% and 25% as large as the objective volatility, compared with 34% in "Kenya."

Table 8: **Accounting Exercises: Parameters**

(a) **Baseline: Country-Specific Volatility and Uncertainty**

| Parameter | Description | "US" | "Poland" | "Kenya" |
|---|---|---|---|---|
| $\hat{A}$ | Relative TFP | 1.000 | 0.534 | 0.075 |
| $f$ | Fixed cost | 10.4 | 3.4 | 0.05 |
| $\tilde{\sigma}$ | Subjective volatility | 0.04 | 0.09 | 0.25 |
| $\sigma$ | Objective volatility | 0.29 | 0.38 | 0.73 |
| $\tilde{\sigma}/\sigma$ | Overprecision ratio | 0.16 | 0.25 | 0.34 |

(b) **Country-Specific Volatility, No Overprecision**

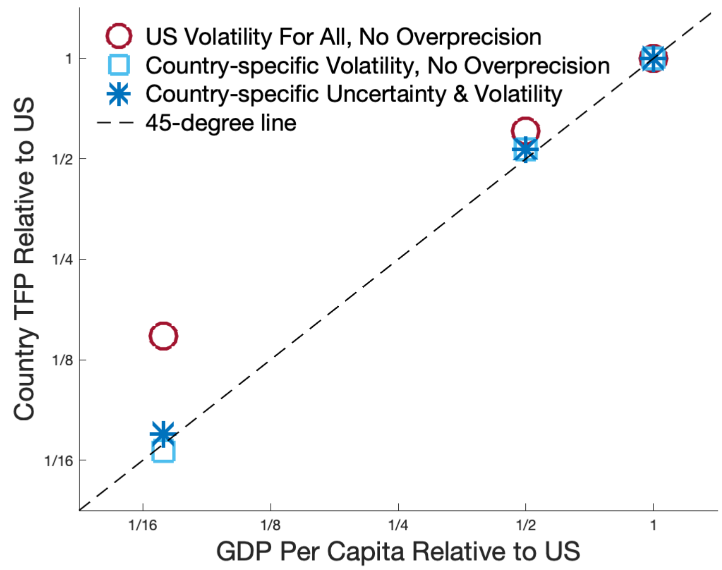
| Parameter | Description | "US" | "Poland" | "Kenya" |
|---|---|---|---|---|
| $\hat{A}$ | Relative TFP | 1.000 | 0.534 | 0.067 |
| $f$ | Fixed cost | 28.7 | 12.1 | 0.88 |
| $\sigma$ | Objective volatility | 0.28 | 0.37 | 0.73 |

(c) **"US" Volatility, No Overprecision**

| Parameter | Description | "US" | "Poland" | "Kenya" |
|---|---|---|---|---|
| $\hat{A}$ | Relative TFP | 1.000 | 0.607 | 0.147 |
| $f$ | Fixed cost | 28.7 | 14.3 | 2.00 |
| $\sigma$ | Objective volatility | 0.28 | 0.28 | 0.28 |

**Notes:** This table shows the parameters that match the four data moments for three versions of our development accounting exercise. Table 8a shows the results from the full exercise where we match relative GDP per capita, volatility (average absolute forecast errors), uncertainty, and the firm exit rate. The version in Table 8b sets the subjective volatility $\tilde{\sigma}$ equal to the objective volatility, and ignores subjective uncertainty. The version in Table 8c assumes volatility across all countries is equal at the "US" level.

Figure 5: **Relative TFP $\hat{A}$ 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 7 for more about the relative GDP per capita statistics that we target.

To trace out how uncertainty and volatility matter, we plot the relative TFP parameters for the "US," "Poland," and "Kenya" against their relative GDP per capita in Figure 5. The figure shows two key results:

1. We infer *lower* TFP for "Kenya" and "Poland" when we recognize that sales are more volatile there than in the "US." In the figure, the red circles are above the light blue squares. Both sets of estimates come from accounting exercises that assume away overprecision, but the red squares also ignore cross-country differences in volatility.

2. We infer *higher* TFP for "Kenya" and "Poland" (minimally for the latter) when we let managers be overprecise by matching both the level of uncertainty and volatility in each country. In the figure, the blue asterisks are between the light blue squares and the red circles.

In terms of magnitude, matching the level of volatility in each country lowers our inferred TFP for "Poland" by about 12% and for "Kenya" by 55%, compared to the version that assumes uniformly low volatility at the "US" level. Allowing for differences in overprecision by matching also the level of uncertainty raises our inferred TFP for "Poland" by about 0.1% and for "Kenya" by 12%.

Why do our inferences about cross-country TFP change when we acknowledge or ignore cross-country differences in uncertainty and volatility? The answer involves the real investment and entry/exit options that characterize our model. The frictions that generate those options make managers' payoffs (in the form of firm value) convex in the firm's profitability $\log(z)$ as Figure 5a shows. The same is true for incumbent managers' demand for capital in the region where they remain in the market and for entrants, as Figure 5b shows. These convex payoffs and decision rules mean, first, that the real options in the model become more valuable to the manager when (subjective) uncertainty about future profitability is higher. Second, actually making profitability more volatile lets a few lucky businesses who receive large positive shocks grow, invest, and dominate the market.

The second effect explains why we need to infer lower aggregate TFP for "Poland" and "Kenya" when we ask the model to give them higher volatility than the "US". Under higher volatility, some firms in those countries get very positive shocks, invest, and grow large. Invested capital and GDP rise relative to the "US" where volatility is lower and those hugely positive shocks are much rarer. To counteract this volatility effect, our accounting exercise infers that TFP must drop in "Poland" and "Kenya" to generate GDP per capita, respectively, 0.50 and 0.07 times as large as in the "US."[13]

The first (real options valuation) effect explains why letting managers be overprecise – and more so in rich countries – pushes back against the volatility effect. Overprecise managers undervalue the real options embedded in the firm. In fact, they undervalue the firm itself (see Figure 5a) because they assign too low a probability to the arrival of large positive shock that leads to high investment and firm value. That means the option to enter or remain in the market is not valuable to overprecise managers unless current profitability $\log(z)$ is already high and the option is well in-the-money. They prefer to liquidate the firm or simply not enter the market unless the firm is highly profitable, so firms that do operate are more profitable on average. We can see this in Figure 5b where capital demand drops to zero faster for the overprecise manager as we go towards lower levels of profitability on the horizontal axis. This effect resembles the mechanism in Kochen (2022), whereby young firms that are uncertain about their profitability have an incentive to stay in the market and learn about their future business prospects.

Overprecision also raises capital reallocation because it makes managers undervalue the option to wait before adjusting the firm's capital see Abel and Eberly, 1996, and Abel et al., 1996). They invest and disinvest readily in response to shocks and stay closer to the firm's optimal static scale just as in Barrero (2022). More reallocation (and less

[13]Frictions to investment in our model also 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 (e.g., see Bento and Restuccia (2017) and David and Venkateswaran (2019)) to firm profitability limit the impact of static misallocation in our model.

static misallocation) makes the economy more efficient. Improved selection and greater reallocation push GDP up when managers are overprecise. And since overprecision is more severe in rich countries, GDP per capita rises in the “US” relative to “Kenya”, and (to a lesser degree) “Poland.” Our accounting exercise infers, therefore, that aggregate TFP must rise in “Kenya” compared to a world where poor-country firms are volatile but overprecision is uniformly (and non-existent) across countries.

The volatility and real-options valuation effects in our paper relate closely to those described by Bloom (2009). When there is an uncertainty/volatility shock in his paper, the real option to wait (see also Bachmann and Bayer, 2013) becomes more valuable and aggregate output contracts. But then it rebounds because the increased volatility means some firms in the economy get positive shocks and grow in response. In our setting, those two effects manifest themselves by changing our inference of countries’ TFP, rather than by generating aggregate fluctuations.

### 6.3 Robustness [Preliminary and incomplete]

The results from our accounting exercises quantify how much uncertainty matters in high- versus low-volatility environments. In the presence of real investment and entry/exit options, it can change our inference of aggregate TFP by double digit percentages.

So far we presupposed managers face a fixed set of frictions and real options when they choose to start or keep a firm, and when they decide how much to invest. We would like to estimate and characterize the frictions to investment in each country jointly with TFP, uncertainty, and volatility. The fact that we only have a short panel with little information about inputs and output in the World Bank survey data makes that estimation infeasible, unfortunately.

Instead, this section tests the sensitivity of our results to the parametric assumptions in Table 6 and to choices related to our target moments. Doing so points us to the economic mechanisms that power the volatility and real-options effects behind our key results.

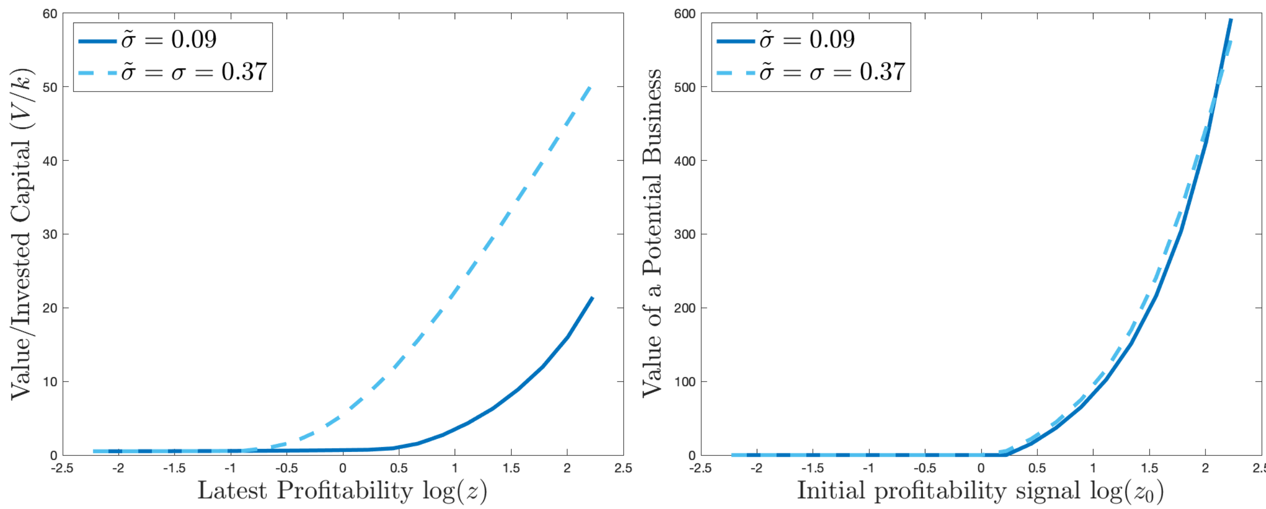
Lowering the persistence of profitability shocks, $\rho$ will dampen both the volatility and real options effects. The reason is persistence makes profitability more important of a variable for the optimal investment program, and therefore its distribution matters more. With zero persistence, profitability $z$ ceases to be a state variable altogether.

If we double the entry/exit rate of our hypothetical economies to 10% per half-year, we amplify the effect of overprecision because entry/exit decisions and therefore the selection effect becomes larger. In such case, overprecision raises TFP in “Poland” by about 13% and 43%, compared with 0.1% and 12% in our baseline calibration.

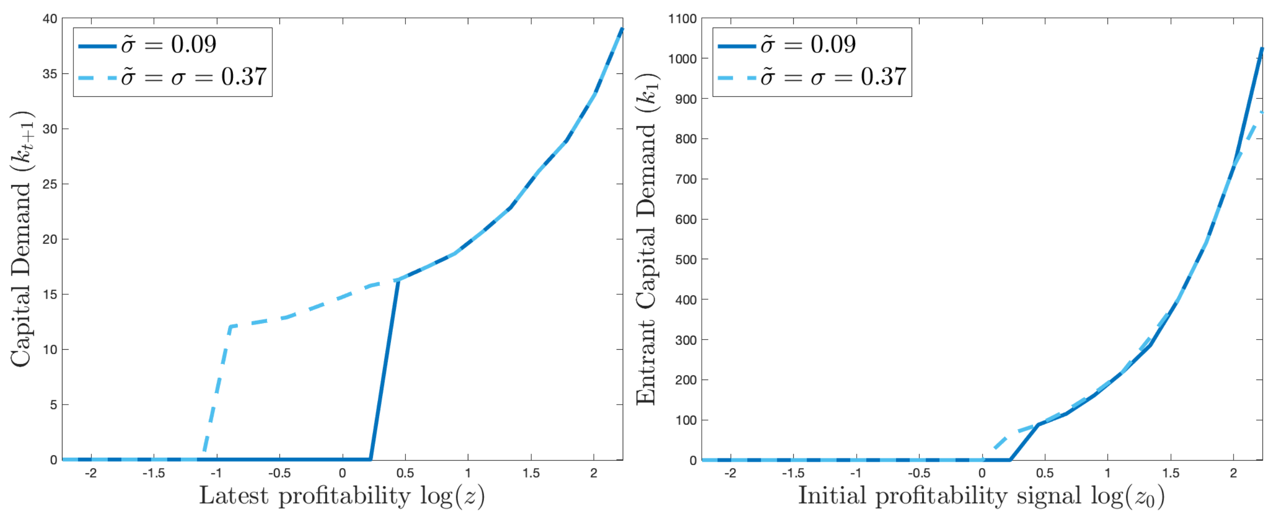
The nature and magnitude of frictions to investment matters for the convexity of

Figure 6: **Convex Payoffs and Decision Rules in the Model**

(a) **Firm Value is Convex in Profitability**




(b) **Demand for Capital is Convex in Profitability**




**Notes:** The top panels plot firm value for incumbents (relative to a given level of invested capital) and for entrants as a function of profitability $\log(z)$. The bottom panels show capital demand (imputed to zero when managers choose to liquidate the firm or remain out of the market), again, as a function of profitability $\log(z)$. The plots in this figure come from the value and investment policy functions for firms in "Poland," comparing the cases where managers perceive uncertainty based on our calibrated value of $\tilde{\sigma}$ or under rational expectations $\sigma$.

firm value and optimal investment decisions. We test whether changing the nature of adjustment costs, such as allowing for smooth convex costs, matters. We also test how bigger costs of starting a firm, $\psi^e$ in poor countries matters. On one hand, those costs deter investment and could lead us to infer higher TFP in poor countries. But they also make entrepreur payoffs more convex and could amplify the volatility and real options effects.

Finally, one key assumption we've made so far is that any adjustment costs paid do not consume output and GDP. If overprecise managers adjust the firm's capital stock and liquidate it prematurely, they could overspend on adjustment costs as in Barrero (2022), which would lower GDP by wasting output in countries where overprecision is more severe.

## 7. Concluding remarks

Our paper makes two key contributions to the literature that studies business uncertainty and its impact on capital budgeting decisions.

First, we examine business uncertainty in high-volatility environments by surveying managers across 41 countries, measuring uncertainty and realized volatility (i.e., absolute forecast errors) across a range of economic environments. We validate those data and document large differences in the way managers perceive uncertainty and experience volatility across countries. We document two new empirical regularities. First, uncertainty and volatility decline with GDP per capita. Second, managers in all countries in our data are overprecise: their subjective uncertainty understates realized volatility measured by absolute forecast errors. This bias is stronger in rich, low-volatility countries where managers underestimate their firm's absolute forecast errors by a larger percentage.

Second, we build a dynamic model featuring real investment and entry/exit options to quantify the implications of our new cross-country facts. We model high- and low-volatility countries based on our cross-country evidence and ask, how much do differences in volatility and uncertainty matter when managers face frictions to investment and real options? We conduct development accounting exercises, weighing up our empirical facts by how much they change our inference of aggregate TFP. High volatility in poor countries raises a puzzle, because under the convex payoffs and decisions delivered by our real options model it gives a few lucky firms in poor-country firms the opportunity to grow and invest. Reconciling that high volatility with poor countries' low GDP per capita requires lower TFP in those countries, compared to a world with uniformly low volatility. Overprecision pushes the other way, because it makes managers undervalue the firm's real options and thereby improves selection and reallocation. Those effects are stronger in rich countries, where overprecision is more severe, so overprecision implies smaller TFP gaps between rich and poor countries.

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# A. Online Appendix — Not Intended for Publication

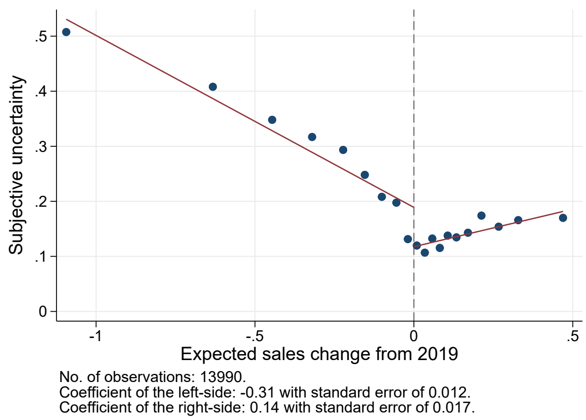
## A.1 Description of data cleaning and preparation procedures

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

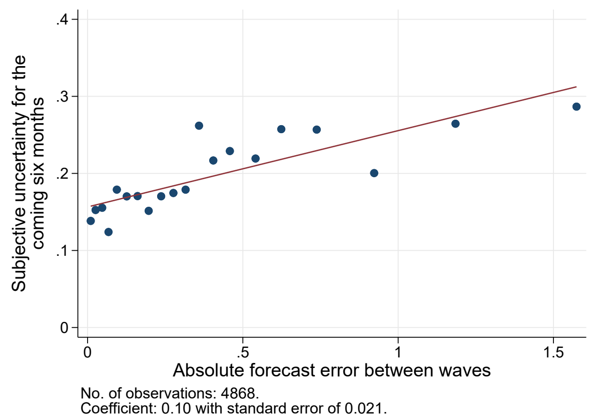
- When a respondent provides the subjective probability for each scenario and the sum of the probabilities is between 50 and 150 (but not exactly 100), we rescale the probabilities to add to 100.
- When a respondent provides three support points for the subjective distribution but some or all of the 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.[14]
- 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 (14.6% of the raw sample) 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.

Figure A1: Uncertainty reflects shifts in the business environment.

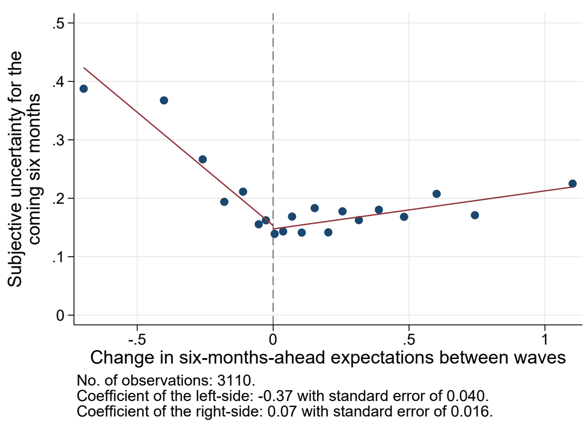
(a) Subjective uncertainty has a negative correlation with expected sales.




(b) Uncertainty rises with past absolute forecast errors.




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

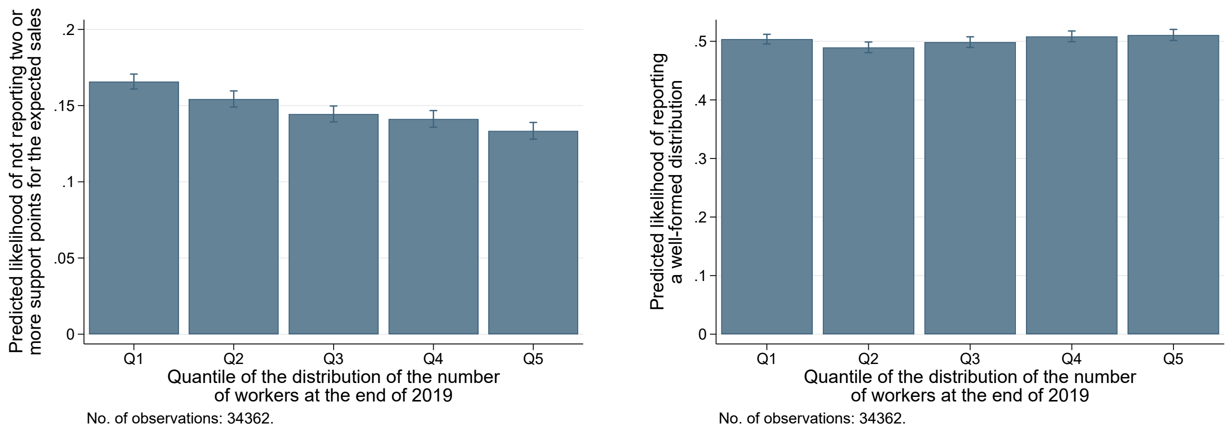



**Notes:** Panel a shows an employment-weighted binned scatter plot of firm-level subjective uncertainty against sales expectations pooling across all country-wave cross-sections. Panels b shows a binned scatter plot of subjective uncertainty about six-months-ahead sales as expressed in follow-up interviews 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 A2: The likelihood of eliciting well-formed subjective distributions for own-firm sales growth increases with the size of the firm.

(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.



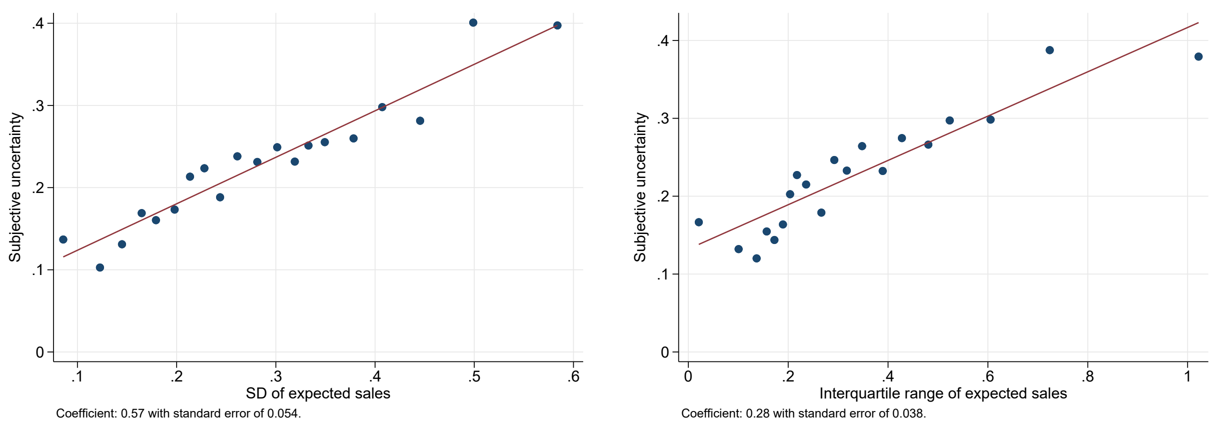

**Notes:** In panel a the dependent variable is an indicator that equals 1 when the subjective distribution has two or more missing support points for the expected sales growth, and 0 otherwise. In panel b the dependent variable is an indicator that equals 1 when the firm reports a well-formed subjective 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 quantile, keeping the other regressors constant.

## A.2 Additional results

Figure A3: More uncertainty about future sales growth in country-sectors with more dispersion in expectations.

(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.

[14] 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 A1: **Uncertainty Declines with GDP per Capita: The Role of Institutions**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Subjective uncertainty | | | |
| GDP per capita (log) | -0.051*** | -0.034*** | -0.053*** | -0.018** |
| | (0.012) | (0.010) | (0.010) | (0.007) |
| Absolute change in sales | | 0.088*** | | 0.105*** |
| | | (0.011) | | (0.008) |
| GDP SD 09-19 / Mean | | 1.786*** | | 1.276*** |
| | | (0.239) | | (0.186) |
| SD (arc) change in sales same country-wave-sector | | 0.105** | | 0.090** |
| | | (0.043) | | (0.040) |
| Exchange rate volatility last 30 days | | 0.234 | | 0.607** |
| | | (0.190) | | (0.273) |
| "People can be trusted" (WVS) | 0.111 | 0.096 | | |
| | (0.110) | (0.071) | | |
| "There is corruption in my country" (WVS) | -0.010 | 0.030** | | |
| | (0.009) | (0.011) | | |
| Individualism (Hofstede) | | | -0.000 | -0.000 |
| | | | (0.001) | (0.000) |
| Exchange rate regime dummies | No | Yes | No | Yes |
| Mobility and size | Yes | Yes | Yes | Yes |
| Sector and quarter dummies | Yes | Yes | Yes | Yes |
| Observations | 11,895 | 11,895 | 21,279 | 21,279 |
| Within $R^2$ | 0.062 | 0.165 | 0.084 | 0.199 |
| No. of clusters | 86 | 86 | 135 | 135 |

**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." The individualism indicator comes from Hofstede Insights. We take the country level indicator available in their website as consulted on December 21, 2023. *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. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

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

Table A2: **Expectations Show No Clear Relationship with GDP per Capita**

| | (1) | (2) | (3) |
|---|---|---|---|
| | | **Expecations** | |
| GDP per capita (log) | 0.019 | 0.000 | -0.009 |
| | (0.012) | (0.011) | (0.017) |
| Absolute change in sales | | -0.165*** | -0.162*** |
| | | (0.020) | (0.020) |
| Exchange rate volatility last 30 days | | | -0.512 |
| | | | (1.105) |
| SD (arc) change in sales same country-wave-sector | | | -0.186* |
| | | | (0.107) |
| GDP SD 09-19 / Mean | | | -2.137*** |
| | | | (0.611) |
| GDP annual growth SD 09-19 | | | 0.031*** |
| | | | (0.006) |
| Exchange rate regime dummies | No | No | Yes |
| Mobility and size | Yes | Yes | Yes |
| Sector and quarter dummies | Yes | Yes | Yes |
| Observations | 26,734 | 25,892 | 20,854 |
| Within $R^2$ | 0.015 | 0.071 | 0.132 |
| No. of clusters | 195 | 195 | 124 |

**Notes:** Linear regressions with expectations about six-months-ahead sales (relative to the same period in 2019) as dependent variable. *Transit mobility* is the level of mobility around transit stations in the 30 days before the interview according to Google Mobility Trends. Heteroskedasticity-robust standard errors are clustered at the country-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: **Survey country and time coverage in each region**

| | 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 |
| Uzbekiztan | | | | | | X | | |
| Latin America | | | | | | | | |
| Brazil | | X | | | | | | |
| El Salvador | | | | X | | | | |
| Guatemala | | | | X | | | | |
| Honduras | | | | X | | | | |
| Nicaragua | | | | X | | | | |
| North Africa | | | | | | | | |
| Tunisia | X | | | | | | | |
| South Asia | | | | | | | | |
| Bangladesh | | X | | | | | | |
| India | X | | | | | | | |
| Nepal | X | | | | | | | |
| Sub-Saharan Africa | | | | | | | | |
| Ghana | X | X | | | | | | |
| Kenya | | X | X | | | | | |
| Madagascar | | X | | X | | | | |
| Malawi | | | X | | | | | |
| Nigeria | | X | | | | | | |
| Senegal | X | | | X | | | | |
| Sierra Leone | | | X | X | | | | |
| South Africa | X | | X | | | | | |
| Tanzania | | X | X | | | | | |

Table A4: **Number of panel observations by country and wave**

| | No. of observations | Wave 1 | Wave 2 |
|---|---|---|---|
| Bulgaria | 218 | Quarter 1 | Quarter 3 |
| Ghana | 21 | Quarter 1 | Quarter 2 |
| Indonesia | 357 | Quarter 1 | Quarter 3 |
| Kenya | 429 | Quarter 2 | Quarter 3 |
| Madagascar | 122 | Quarter 2 | Quarter 4 |
| Poland | 346 | Quarter 2 | Quarter 3 |
| Romania | 284 | Quarter 1 | Quarter 4 |
| Senegal | 227 | Quarter 1 | Quarter 4 |
| Sierra Leone | 33 | Quarter 4 | Quarter 4 |
| South Africa | 176 | Quarter 1 | Quarter 3 |
| Tanzania | 44 | Quarter 2 | Quarter 3 |
| Turkey | 149 | Quarter 2 | Quarter 4 |
| Vietnam | 355 | Quarter 2 | Quarter 3 |

Table A5: **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 | | | | | | | | | |
| Quarter 1 | 523 | 40.7 | 35.6 | 23.7 | 39.0 | 2.3 | 8.6 | 38.0 | 7.3 |
| Quarter 3 | 429 | 40.3 | 32.2 | 27.5 | 38.5 | 3.0 | 7.0 | 37.5 | 8.9 |
| Malaysia | | | | | | | | | |
| Quarter 3 | 632 | 22.0 | 27.1 | 50.9 | 24.8 | 22.0 | 4.0 | 30.9 | 13.9 |
| Mongolia | | | | | | | | | |
| Quarter 4 | 199 | 39.7 | 46.7 | 13.6 | 30.7 | 37.7 | 4.0 | 6.0 | 21.6 |
| Vietnam | | | | | | | | | |
| Quarter 2 | 413 | 47.2 | 30.8 | 22.0 | 41.2 | 21.5 | | 24.0 | 13.3 |
| Quarter 3 | 417 | 52.0 | 28.8 | 19.2 | 39.8 | 22.5 | | 22.8 | 12.0 |
| Quarter 4 | 427 | 50.8 | 27.6 | 21.5 | 40.5 | 21.8 | | 21.8 | 12.9 |
| Bulgaria | | | | | | | | | |
| Quarter 1 | 571 | 49.4 | 37.0 | 13.7 | 32.2 | 20.5 | 6.8 | 23.6 | 16.8 |
| Quarter 3 | 459 | 52.5 | 37.3 | 10.2 | 29.8 | 17.4 | 7.4 | 26.6 | 18.7 |
| Kosovo | | | | | | | | | |
| Quarter 2 | 574 | 74.0 | 22.3 | 3.7 | 18.1 | 19.7 | 9.9 | 5.1 | 47.2 |
| Poland | | | | | | | | | |
| Quarter 2 | 802 | 32.8 | 47.3 | 20.0 | 37.8 | 24.2 | 3.5 | 22.1 | 12.5 |

Table A5: **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 |
| Quarter 3 | 402 | 34.6 | 48.0 | 17.4 | 42.5 | 22.6 | 4.7 | 19.2 | 10.9 |
| Quarter 4 | 328 | 37.5 | 43.9 | 18.6 | 43.3 | 23.2 | 4.0 | 19.2 | 10.1 |
| Romania | | | | | | | | | |
| Quarter 1 | 549 | 41.3 | 44.4 | 14.2 | 21.1 | 16.4 | 12.2 | 32.8 | 17.5 |
| Quarter 4 | 371 | 47.4 | 41.5 | 11.1 | 20.2 | 15.4 | 11.6 | 35.3 | 17.5 |
| Turkey | | | | | | | | | |
| Quarter 2 | 628 | 40.8 | 39.5 | 19.7 | 45.1 | 9.7 | 5.3 | 24.7 | 15.1 |
| Quarter 4 | 819 | 47.7 | 36.4 | 15.9 | 25.4 | 9.3 | 16.6 | 25.6 | 23.1 |
| Brazil | | | | | | | | | |
| Quarter 2 | 326 | 28.8 | 38.3 | 32.8 | 44.5 | 21.2 | 4.3 | 5.2 | 22.4 |
| El Salvador | | | | | | | | | |
| Quarter 4 | 305 | 39.0 | 35.4 | 25.6 | 47.9 | 33.1 | 2.3 | 13.4 | 2.6 |
| Guatemala | | | | | | | | | |
| Quarter 4 | 149 | 38.9 | 35.6 | 25.5 | 38.3 | 34.2 | 5.4 | 15.4 | 5.4 |
| Honduras | | | | | | | | | |
| Quarter 4 | 116 | 39.7 | 40.5 | 19.8 | 23.3 | 46.6 | 2.6 | 22.4 | 5.2 |
| Nicaragua | | | | | | | | | |

Table A5: **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 |
| Quarter 4 | 135 | 40 | 45.9 | 14.1 | 31.1 | 33.3 | 10.4 | 22.2 | 2.2 |
| Tunisia | | | | | | | | | |
| Quarter 1 | 439 | 22.3 | 28.9 | 48.7 | 54.9 | 12.5 | 7.5 | 19.8 | 5.2 |
| Bangladesh | | | | | | | | | |
| Quarter 2 | 172 | 66.9 | 27.3 | 5.8 | 67.4 | 2.9 | 8.7 | 5.8 | 15.1 |
| India | | | | | | | | | |
| Quarter 1 | 571 | 23.6 | 43.6 | 32.7 | 61.8 | 0.9 | 0.9 | 29.6 | 6.5 |
| Nepal | | | | | | | | | |
| Quarter 1 | 288 | 71.5 | 21.9 | 6.6 | 18.1 | 37.5 | 18.1 | 13.9 | 12.5 |
| Ghana | | | | | | | | | |
| Quarter 1 | 47 | | 59.6 | 40.4 | 19.1 | 14.9 | 4.3 | 31.9 | 29.8 |
| Quarter 2 | 72 | | 69.4 | 30.6 | 15.3 | 11.1 | 4.2 | 31.9 | 37.5 |
| Kenya | | | | | | | | | |
| Quarter 2 | 789 | 41.6 | 37.4 | 21.0 | 18.1 | 13.3 | 17.7 | 26.4 | 24.5 |
| Quarter 3 | 658 | 48.8 | 30.2 | 21.0 | 19.1 | 12.9 | 14.7 | 27.8 | 25.2 |
| Madagascar | | | | | | | | | |
| Quarter 2 | 257 | 38.5 | 38.1 | 23.3 | 10.5 | 13.2 | 12.8 | 44.0 | 13.2 |

Table A5: **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 |
| Quarter 4 | 350 | 50 | 32.9 | 17.1 | 12 | 8 | 8 | 50.3 | 18.3 |
| Malawi | | | | | | | | | |
| Quarter 3 | 647 | 68.8 | 25.0 | 6.2 | 11.9 | 29.7 | 21.9 | 29.4 | 7.1 |
| Nigeria | | | | | | | | | |
| Quarter 2 | 325 | 47.4 | 49.8 | 2.8 | 17.5 | 9.5 | 8.3 | 30.2 | 34.5 |
| Senegal | | | | | | | | | |
| Quarter 1 | 436 | 55.0 | 29.6 | 15.4 | 31.2 | 23.9 | 3.0 | 21.6 | 20.4 |
| Quarter 4 | 328 | 64.6 | 25 | 10.4 | 30.8 | 24.4 | 2.7 | 20.1 | 22.0 |
| Sierra Leone | | | | | | | | | |
| Quarter 3 | 116 | 76.7 | 16.4 | 6.9 | 8.6 | 22.4 | 13.8 | 43.1 | 12.1 |
| Quarter 4 | 96 | 82.3 | 11.5 | 6.3 | 11.5 | 21.9 | 20.8 | 40.6 | 5.2 |
| South Africa | | | | | | | | | |
| Quarter 1 | 1035 | 57.6 | 37.5 | 4.9 | 16.9 | 10.0 | 11.0 | 34.1 | 27.9 |
| Quarter 3 | 242 | 66.5 | 30.2 | 3.3 | 19.4 | 8.7 | 9.9 | 36.0 | 25.2 |
| Tanzania | | | | | | | | | |
| Quarter 2 | 193 | 51.8 | 38.9 | 9.3 | 40.4 | 14.5 | 14.0 | 21.2 | 9.8 |
| Quarter 3 | 301 | 83.7 | 13.6 | 2.7 | 33.9 | 7.0 | 13.3 | 11.3 | 34.6 |

Table A6: **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 there are 850 observations where the date of the interview is missing. 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.

Table A7: **Summary statistics for sales outcomes in the coming six months and their corresponding probabilities**

| | Sales growth forecast | | Support point probability | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Full sample | | | | |
| Pessimistic | −0.452 | 0.557 | 27.5 | 15.9 |
| Central | −0.077 | 0.416 | 38.8 | 16.7 |
| Optimistic | 0.155 | 0.298 | 34.2 | 15.7 |
| Apr-Jun 2020 | | | | |
| Pessimistic | −0.655 | 0.598 | 30.2 | 17.9 |
| Central | −0.247 | 0.494 | 37.8 | 18.1 |
| Optimistic | 0.083 | 0.374 | 32.2 | 16.4 |
| Jul-Sep 2020 | | | | |
| Pessimistic | −0.572 | 0.583 | 28.7 | 14.2 |
| Central | −0.178 | 0.451 | 41.0 | 15.4 |
| Optimistic | 0.084 | 0.321 | 31.0 | 13.8 |
| Oct-Dec 2020 | | | | |
| Pessimistic | −0.463 | 0.532 | 27.2 | 13.9 |
| Central | −0.074 | 0.381 | 38.5 | 13.9 |
| Optimistic | 0.138 | 0.286 | 34.6 | 14.1 |
| Jan-Mar 2021 | | | | |
| Pessimistic | −0.421 | 0.531 | 27.3 | 15.9 |
| Central | −0.058 | 0.376 | 39.0 | 17.5 |
| Optimistic | 0.149 | 0.280 | 34.0 | 16.3 |
| Apr-Jun 2021 | | | | |
| Pessimistic | −0.182 | 0.340 | 23.6 | 14.7 |
| Central | 0.058 | 0.307 | 40.4 | 17.0 |
| Optimistic | 0.208 | 0.240 | 36.7 | 16.6 |
| Jul-Sep 2021 | | | | |
| Pessimistic | −0.379 | 0.558 | 27.7 | 16.6 |
| Central | 0.002 | 0.389 | 37.6 | 17.4 |
| Optimistic | 0.218 | 0.252 | 35.1 | 16.0 |
| Oct-Dec 2021 | | | | |
| Pessimistic | −0.418 | 0.542 | 21.4 | 18.7 |
| Central | 0.002 | 0.278 | 38.8 | 20.7 |
| Optimistic | 0.246 | 0.212 | 39.8 | 21.2 |
| Jan-Mar 2022 | | | | |
| Pessimistic | 0.045 | 0.098 | 33.4 | 21.4 |
| Central | 0.162 | 0.191 | 35.5 | 20.6 |
| Optimistic | 0.314 | 0.185 | 34.8 | 18.3 |

**Notes:** The table reports means and standard deviations (SD) of sales outcomes associated with the three support points of businesses' subjective probability distributions over future own-firm sales and their corresponding probabilities. We do not use employment weights to compute those statistics. The sample includes all responses for which we can compute a measure of subjective uncertainty (i.e., excluding distributions for which two or more support points are missing or with zero subjective uncertainty). Sales outcomes in each scenario are for a 6-month look-ahead period, and sales levels are expressed relative to the same period of 2019.

Table A8: **Summary statistics for sales expectations (forecasts) subjective uncertainty**

| | Average expectation for the change in sales | Average subjective uncertainty |
|---|---|---|
| Full sample | -0.06 | 0.21 |
| | (0.354) | (0.202) |
| Apr-Jun 2020 | - 0.22 | 0.26 |
| | (0.455) | (0.224) |
| Jul-Sep 2020 | -0.12 | 0.24 |
| | (0.375) | (0.196) |
| Oct-Dec 2020 | -0.10 | 0.23 |
| | (0.350) | (0.190) |
| Jan-Mar 2021 | -0.05 | 0.18 |
| | (0.296) | (0.193) |
| Apr-Jun 2021 | 0.06 | 0.14 |
| | (0.238) | (0.130) |
| Jul-Sep 2021 | 0.01 | 0.21 |
| | (0.327) | (0.233) |
| Oct-Dec 2021 | 0.10 | 0.21 |
| | (0.284) | (0.178) |
| Jan-Mar 2022 | 0.16 | 0.10 |
| | (0.130) | (0.075) |

**Notes:** The table reports employment-weighted means and standard deviations (SD) of the first and second moments of the sample of subjective probability distributions. We report standard deviations in parenthesis. The forecasting period corresponds to a 6-month look-ahead horizon relative to the same period in the prior year.