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The Macroeconomics of Data: Scale, Product Choice, and Pricing in the Information Age

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Abstract

We document a substantial rise in the accuracy of U.S. firms' expectations since the early 2000s, closely linked to firm-size dynamics and consistent with major advances in data-processing technologies. To study the macroeconomic implications, we develop a model of information production, in which information enables firms to optimize their *scale*, *product choice*, and *pricing* strategies. While information enhances the efficiency of resource allocation, it also facilitates price discrimination. The laissez-faire equilibrium is inefficient, warrants corrective policy interventions, and advances in data-processing technologies have ambiguous effects on social welfare. Calibrating our model to U.S. firm-level data, we find that data-processing advances have significantly increased TFP over the past two decades (5.3-6.7%), primarily by helping firms determine their optimal scale. Yet, the welfare benefits of these improvements have been modest (0.1-2.1%). Restricting data use, especially by large firms, could trigger larger welfare gains.

JEL codes: E10, E60, C53, D83, D84

Keywords: data economy, expectations, information frictions, product choice, price discrimination, rent extraction, misallocation, optimal policy, data regulation

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1 Introduction

Advances in data-processing technologies are widely believed to have the potential to reshape most economic interactions. Consistent with this view, the past two decades have seen a substantial rise in the share of firms that systematically use data to inform their economic decision-making. A simple estimate based on survey data from a sample of medium-to-large firms indicates that this share has more than doubled in the past ten years alone (Mckinsey and Company., 2023). As of today, approximately 40-75 percent of manufacturing firms employ some form of *data-driven decision-making* (Brynjolfsson and McElheran, 2024).[1]

Despite the substantial rise in data use by firms, the macroeconomic consequences of these developments are, nevertheless, not fully understood. Has the apparent rise in data use led to an improved allocation of resources across and within firms, sizable enough to affect economy-wide dynamics? Or, have these developments allowed firms to extract ever larger rents from consumers, diluting their potential welfare benefits? Answers to these questions are important not only to understand the developments of the recent decades, but also to design effective regulatory frameworks that will govern the data economy of the future.

In this paper, we explore answers to these questions. Throughout, we view *data as information* that helps firms predict economic fundamentals (Baley and Veldkamp, 2025). The rationale for this view is both *practical*—changes in information can be measured by changes in the accuracy of firms' expectations—and *conceptual*—since the seminal work of Lucas (1972), the role of information has been shown to be central to understanding macroeconomic dynamics.[2] Using micro-level data on firms' expectations, we document a substantial increase in the accuracy of U.S. firms' information since the early 2000s. This improvement is closely linked to firm-size dynamics, and it aligns with a significant rise in firms' data use.

Our main contribution is to develop a *unifying*, quantitative-theoretical framework to explore the macroeconomic consequences of these developments. In our model, information production helps firms optimize their *scale*, *product choice*, and *pricing strategies*. These channels are thought to be among the most prominent ways by which data and information technologies have transformed firm behavior over the past decades.[3] In our framework, information has a dual role. On the one hand, it boosts the allocative efficiency of resources across and within firms. But, on the other hand, it also facilitates price discrimination, which may be socially undesirable. The net effect of advances in data-processing technologies depends on the bal-

[1] See Brynjolfsson and McElheran (2016) and Goldfarb *et al.* (2015) for overviews on adoption rates.

[2] See, e.g., Lorenzoni (2009), Blanchard *et al.* (2013), Chahrour and Jurado (2018), Angeletos and Lian (2016), Angeletos *et al.* (2021), among others.

[3] Feng *et al.* (2020) and Babina *et al.* (2024) discuss changes to product design, while Adams *et al.* (2024) documents changes in firms' pricing; Zolas *et al.* (2021) and Jin and McElheran (2024) discuss changes in inputs associated with cloud computing and AI; lastly, O'Neill (2023) presents several business cases.

ance of those two forces. We show that the laissez-faire equilibrium is inefficient, warranting corrective policy regulation. Across a wide range of parameters, our theory lends support to a common concern that firms—particularly large ones—produce and use data excessively (e.g., European Commission Report, 2020).

The aggregate impact of advances in data-processing technologies, as well as the design of optimal corrective policies, depends on several key parameters. To identify them, we employ a calibration strategy that leverages U.S. firm-level data, allowing us to establish sharp bounds on the costs and benefits of technological advancements. Our estimates indicate that data-processing improvements have meaningfully increased total factor productivity (TFP) over the past two decades (5.3-6.7%), primarily by enabling firms to better optimize their scale of operations. However, the corresponding welfare gains have been relatively modest (0.1-2.1%), as much of the benefits have been offset by excessive information production by firms. Our findings underscore the crucial role of corrective data regulation in the information age.

To empirically motivate our work, we use micro-level data on managerial forecasts from the I/B/E/S-Compustat panel. Using the merged firm-level data set, we document a systematic rise in the accuracy of US firms' expectations over time. Over the past two decades, firms' expectations of one-year-ahead revenue, profits, and capital expenditures have all witnessed accuracy increases between 20-50 percent, with similar developments across most sectors. Crucially, we show that this rise in the accuracy of expectations persists even after controlling for the volatility of firm-level and economy-wide shocks, showing that firms have become substantially more informed about future developments since the early 2000s.

We then proceed to study the the cross-sectional determinants of firms' accuracy. Across a range of estimation strategies and controls, we find robust evidence that, all else equal, larger firms are systematically more accurate than smaller ones. The accuracy of firms' expectations exhibits substantial heterogeneity across the size distribution.[4] Through a simple simulation exercise, we show that the bulk of the aggregate improvement in the accuracy of firms' expectations over the past two decades can be accounted for by developments caused by the size-accuracy relationship. In contrast, changes in sectoral composition, or changes in the volatility of outcome variables appear to only play a minor role.

We conduct a comprehensive set of robustness checks, demonstrating that our results hold across alternative measures, model specifications, and with the inclusion of firm-level controls. Crucially, we show that the positive relationship between firm size and accuracy extends to an independent data source—the Duke-Richmond Fed CFO Survey—which captures firms' expectations of macroeconomic outcomes beyond their direct control. This finding bolsters the case that the size-accuracy relationship reflects differences in information quality rather

[4] See also Tanaka *et al.* (2020), Chen *et al.* (2023), and Chen *et al.* (2024).

than differences in the nature or predictability of the outcome variable.

To explore the macroeconomic implications of our findings, we develop a macroeconomic model of information production. We consider an economy populated by heterogeneous consumers with preferences over differentiated varieties supplied by monopolistic firms à la Dixit and Stiglitz (1977). The central friction in our economy is that firms must allocate inputs and price products under uncertainty about technologies and preferences.

In particular, firms are uncertain about their optimal *scale* of operations, as production quantities depend not only on input choices but also on firms' ex-ante unknown productivity state. Firms also face uncertainty about their optimal *product choice*, as they want to customize their varieties to better match ex-ante unknown consumer tastes. Finally, when choosing their *pricing strategies*, firms face heterogeneous consumers who are privately informed about their own individual tastes, creating uncertainty about the best pricing strategy.

A key feature of our framework is that firms can mitigate such uncertainty through costly information production. By expending scarce resources, firms can obtain informative signals about the states of nature governing *demand* and *productivity*. We model advancements in data processing as stemming from either a reduction in the cost of obtaining these signals or an increase in their accuracy. This stylized approach captures key technological developments, such as, e.g., declining computing costs and improvements in processing speeds.[5]

We begin our analysis with a pedagogical *baseline economy*, where firms are exogenously constrained from price discrimination and their use of information is solely benign. In equilibrium, firms select into information production based on ex-ante size differences. Information production facilitates the optimal determination of *scale* and *product choice*, driving growth in firm profits, size, and efficiency, as reflected in firm-level measures of total factor productivity (TFP) and dispersion of marginal revenue products. In general equilibrium, information production enhances aggregate TFP both directly—by improving firm-level efficiency—and indirectly—by reallocating inputs toward better-informed firms. Under this benign view, we show that advances in data-processing technologies unambiguously enhance social welfare.

We next turn to our primary setting, the *rent-extracting economy*, where firms also optimize their *pricing strategies* to engage in price discrimination. Specifically, we allow firms to design optimal trading mechanisms to allocate their varieties to consumers. Due to asymmetric information between firms and consumers, price discrimination introduces a *conflict* between profit maximization and social surplus maximization, leading firms to distort allocations to extract larger rents from consumers. Crucially, information production—through its effect on the degree of asymmetric information—affects the severity of this conflict between profit

[5]See, e.g., Nordhaus (2008), Coyle and Hampton (2024), and Gill *et al.* (2024) for evidence of substantial declines in computing costs and improvements in processing speeds over the past two decades.

and surplus maximization. Consequently, we show that the laissez-faire equilibrium is inefficient, and the welfare effects of technological advances in data processing become ambiguous, providing a strong rationale for regulatory intervention.

We characterize the optimal corrective policy and identify the scenarios in which firms engage in *excessive* information production. This occurs when *rent extraction is severe*, a parameter region where firms' ability to extract rents from consumers grows faster with information than their contribution to social surplus. This finding lends support to the recently discussed and implemented policies, such as the General Data Protection Regulation in the EU, to limit firms' ability to collect, store, and exploit consumer data in ways that fosters discriminatory behavior.[6] However, we also provide conditions under which information production is *insufficient*, providing caution that limiting data use by firms may not always be desirable. Finally, even when information production is excessive, we show that *optimal corrective policy also targets firm-size concentration*, as the distortions introduced through information production intensify with firm scale.

Our rent-extracting framework highlights the different effects that advances in data-processing technologies have on the economy, depending on the exact parameter values governing it, the extent of distortions due to price discrimination, and the stance of corrective policy. To analyze the consequences that advances in data-processing have had on the U.S. economy over the two past decades, we proceed to validate and quantify the implications of such changes for the rent-extracting economy, using our micro-level data set. We proceed in two steps.

First, we show that, consistent with our model predictions for *any extent of price discrimination*, firms that report more accurate expectations allocate inputs more efficiently, adopt more preferred products, are more profitable, and grow faster and larger. Second, we provide bounds on the potential benefits that advances in data-processing have had over the past two decades. To do so, we construct a best- and worst-case scenario with respects to price discrimination. The best-case scenario is isomorphic to our baseline economy, while the worst-case scenario corresponds to the case with the most detrimental rent-extraction.

For plausible parameter values, consistent with the observed increase in accuracy over our sample period, our main estimates document that TFP (household welfare) in the US would have been 5.3-6.7% (0.1-2.1%) lower in 2022 absent the increase in the informativeness of firms. On balance, we find that the lion's share of this rise in TFP (c. 2/3-3/4 of the increase) arises due to improvements in firms' capacity to better determine their optimal scale of operations, with improvements in product design playing distinct secondary role (at most 1/3). Notwithstanding these increases, at the same time, our results show that most of the welfare benefits from this rise in TFP can be eaten up by firms improved capacity to price

[6] See https://gdpr.eu/ for details on GDPR in the European Union.

discriminate. Our quantitative results, thus, highlight the potential central role that optimal data-regulation has in insuring that advances in data-processing technologies result in welfare improvements. Indeed, we show that a simple tax can substantially increase the extent to which TFP improvements translate into welfare improvements in the worst-case scenario.

Finally, we conclude our analysis with two extensions. The first uses scanner-level data for the retail sector to provide a first-pass estimate of where the U.S. economy locates itself within our calibrated range. Matching the estimates in Bornstein and Peter (2024) shows that price discrimination is likely close to that in our worst-case scenario. Clearly, the U.S. economy is comprised of sectors beyond the retail sector for which product-level data is not immediately available. Nevertheless, our estimates do provide an initial (albeit imperfect) gauge of the potential detrimental effects of price discrimination. The second extends our rent-extracting framework with capital and variety accumulation. Both features should, in principle, amplify the economy-wide effects of advances in data-processing. We show that, despite some modest amplifcation, our main results remain robust—TFP advances are estimated to have been meaningful but the welfare benefits have been comparatively more subdued.

Related Literature. In addition to the above cited work, our paper is related to four separate strands of research. We review these in order of proximity below.

First, our work builds on the rapidly expanding macroeconomic literature on the data economy (e.g., Begenau *et al.*, 2018; Farboodi and Veldkamp, 2020, 2024; Eeckhout and Veldkamp, 2023). Baley and Veldkamp (2025) provides a comprehensive overview. Our study departs from this growing body of research by developing a *unifying* macroeconomic framework, disciplined with firm-level data, in which information shapes firm behavior through three distinct channels that have been particularly salient since the early 2000s (e.g., O'Neill, 2023). Our framework allows us to decompose and quantify the consequences that advances in data-processing have had on macroeconomic outcomes through separate channels—and to address the central normative questions about corrective data-regulation policy. Our work is, in particular, closely related to the complementary contributions of David *et al.* (2016) and David and Venkateswaran (2019), who develop a framework and methodology to measure firms' use of information. On the empirical front, their approach primarily infers firms' information use indirectly from stock prices, whereas we take a more direct approach that exploits data on managers' expectations. On the theoretical front, their work centers on the (passive) role that information has on factor misallocation—akin to our *scale channel* of information,—whereas we stress that information also affects firms' product choice and pricing strategies. We further shed light on normative questions, such as whether and how to regulate firms' access to data.

Second, our work naturally relates to an extensive literature in microeconomics on price discrimination, as well as its recent macroeconomic application by Bornstein and Peter (2024), who examine how non-linear pricing affects economy-wide markups and factor misallocation.[7] We contribute to this literature by analyzing the general equilibrium effects of price discrimination in settings in which it interacts with firms' incentives to produce information. In turn, our main normative results—and their implications for policy—build on the broader idea that more accurate information may not be socially desirable in settings with information frictions, as it may exacerbate the distortions that are already present due to these frictions.[8]

Third, our work relates to the growing literature that documents a rise in market power and studies the welfare costs stemming from it (e.g., De Loecker *et al.*, 2020; Edmond *et al.*, 2023; Boar and Midrigan, 2024; Eeckhout *et al.*, 2024). A common theme in this work is that large firms—those that have higher market power and markups—are inefficiently small, precisely because they constrain production to raise prices. By contrast, in our framework, monopolistic firms do not need to constrain production to extract consumer surplus; they can do so through price discrimination instead. Indeed, in the parameter region that is consistent with our firm-level data, we find that large firms are indeed *too large*: optimal corrective policy—besides discouraging firms from producing information—also reduces the firm-size concentration.

Finally, our work contributes to the classic literature on the macroeconomic effects of information frictions, tracing back to Lucas (1972). Notable contributions in this area include Woodford (2002), Mankiw and Reis (2002), Angeletos and Pavan (2007), Ordonez (2009), Lorenzoni (2009), Maćkowiak and Wiederholt (2009), and Angeletos *et al.* (2021), among many others. We emphasize the role that firms' strategic information choices have through pricing and resource-allocation channels in amplifying the aggregate consequences of imperfect information. Our contribution, in this context, is to provide the first, to our knowledge, decomposition and quantification of recent advancements in data-processing technologies, and the associated fall in information frictions, on macroeconomic outcomes.

2 Motivating Evidence

We present new evidence on the accuracy of firm expectations over time and across the firm-size distribution. To start, we use micro data on firm expectations from the I/B/E/S managerial guidance database. The I/B/E/S data set contains, for an individual firm-year, a manager's publicly stated expectation for their firm's revenue, profits, and other performance variables over the next year. We exploit one-year-ahead forecasts made concurrently with the release of

[7]See Varian (1989) for a survey of the classic literature on price discrimination and Kehoe *et al.* (2018) for recent research on how big data may enhance firms' ability to discriminate among consumers.

[8]While this idea has primarily been explored in settings with adverse selection (e.g., Malherbe, 2012; Gorton and Ordonez, 2014; Asriyan *et al.*, 2017; Dang *et al.*, 2020; Daley *et al.*, 2020), the contemporaneous works of Farboodi *et al.* (2025) and Asriyan *et al.* (2025) explore it further within related settings of a price-discriminating monopolist faced with privately informed consumers.

the previous year's financials. We link the I/B/E/S database to Compustat, which provides detailed data on firms' financials. The merged I/B/E/S-Compustat sample covers the period 2002-2022. Appendix A.1 provides more information on the sample construction.

We begin by documenting changes to the accuracy of firms' expectations over time.[9] We focus on one-year-ahead revenue errors, defined as the realization minus its predicted value. A negative error thus corresponds to an over-estimate of future revenue. Panel (a) in Figure 1 showcases the average accuracy of firms' expectations over time. All else equal, over the past two decades, firms' expectations have improved considerably, with an average improvement in one-year-ahead accuracy between 24-41 percent, depending on the accuracy measure used. Firms have, on average, become substantially more accurate over time. Table A.3 in the Appendix confirms this initial finding using regressions of individual errors on time.

A natural candidate explanation for firms' increased accuracy is a decline in economy-wide volatility, often associated with the onset of the Great Moderation (e.g., Arias *et al.*, 2007), facilitating prediction. However, as Table A.4 in the Appendix shows, similar results hold after partialling out *sector×time fixed effects* from firms' errors. Consistent with most of the uncertainty faced by firms being due to *firm-specific* rather than *aggregate* factors (Lucas, 1977), the lion-share of the accuracy increase here arises from improvements in firms' expectations about firm-specific outcomes. Combined with the observation that idiosyncratic volatility has, if anything, increased over our sample period (e.g., Bloom *et al.*, 2018 and Section 3), we conclude that *firms' information* about future revenues has improved considerably.

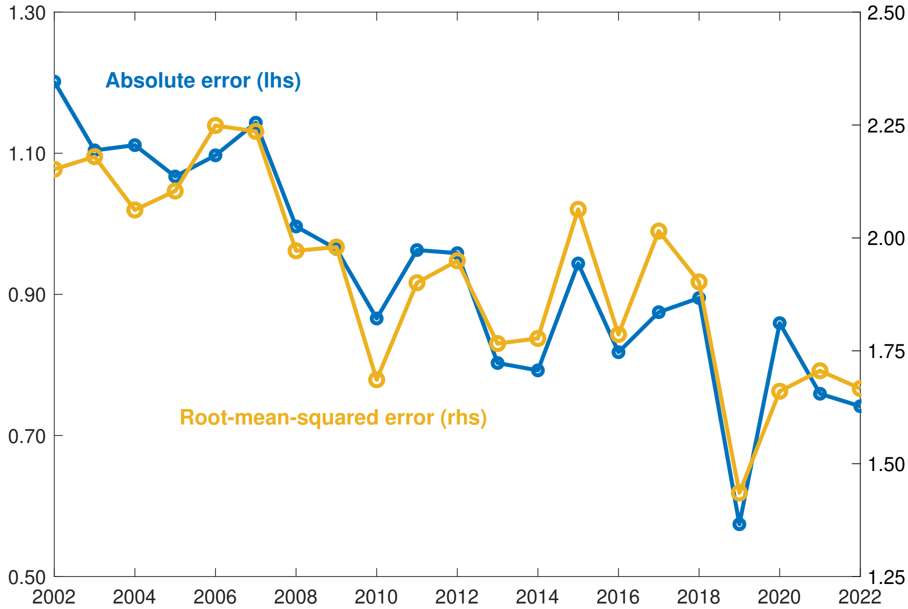
The increased informativeness of firms is suggestive of changes in firm behavior and characteristics. The cross-section of firms can, as such, be revealing about the drivers behind the overall improvement over time. Because of a sizable fixed-cost component to the processing of information (e.g., Brynjolfsson *et al.*, 2008; Bloom *et al.*, 2019), it is natural to ask whether there is a relationship between firm size and the accuracy of firms' expectations. To investigate this question, Panel (a) in Figure 2 plots the difference between the average accuracy of one-year-ahead revenue forecasts within size (employment) quintiles and the overall average taken across all firm sizes. The results in Panel (a) in Figure 2 show a marked, monotone relationship between firm size and the accuracy of firm expectations in the raw data. Throughout, larger firms produce more accurate forecasts—with an especially pronounced difference when moving away from the bottom quintile of the size distribution.

The relationship in Panel (a) may, however, be contaminated by other factors, such as differences in the volatility of revenues across firm size or learning with age, that can simul-

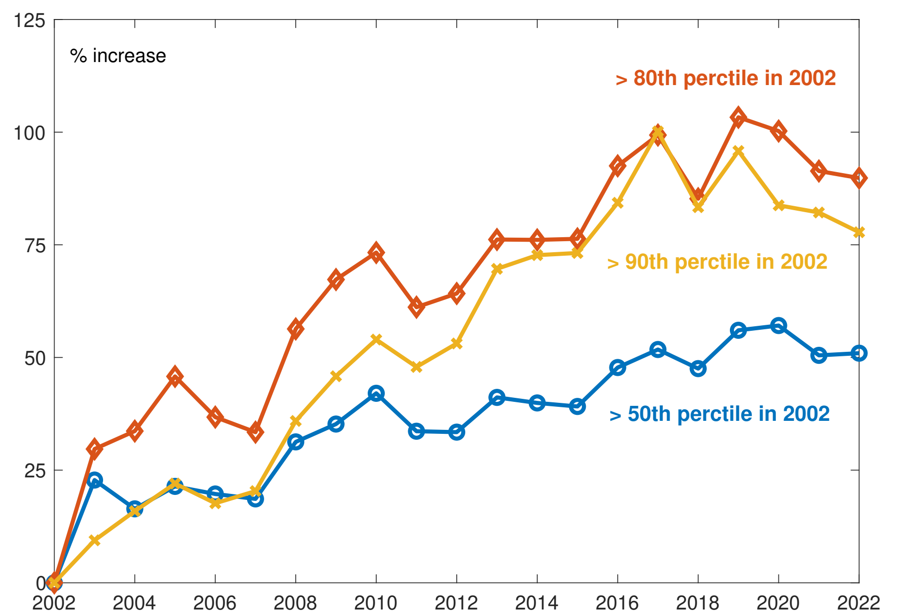
[9]In Appendix A.3, we conduct several data-validation tests, akin to those in Tanaka *et al.* (2020), Chen *et al.* (2023), and Chen *et al.* (2024). In particular, we show that firms' expectations are (close to) unbiased, that more (less) optimistic firms increase (decrease) their use of factors of production, and that positive (negative) surprises result in more (less) inputs being employed subsequently.

Figure 1: Time Evolution of Uncertainty and Size

Panel (a): Uncertainty and time

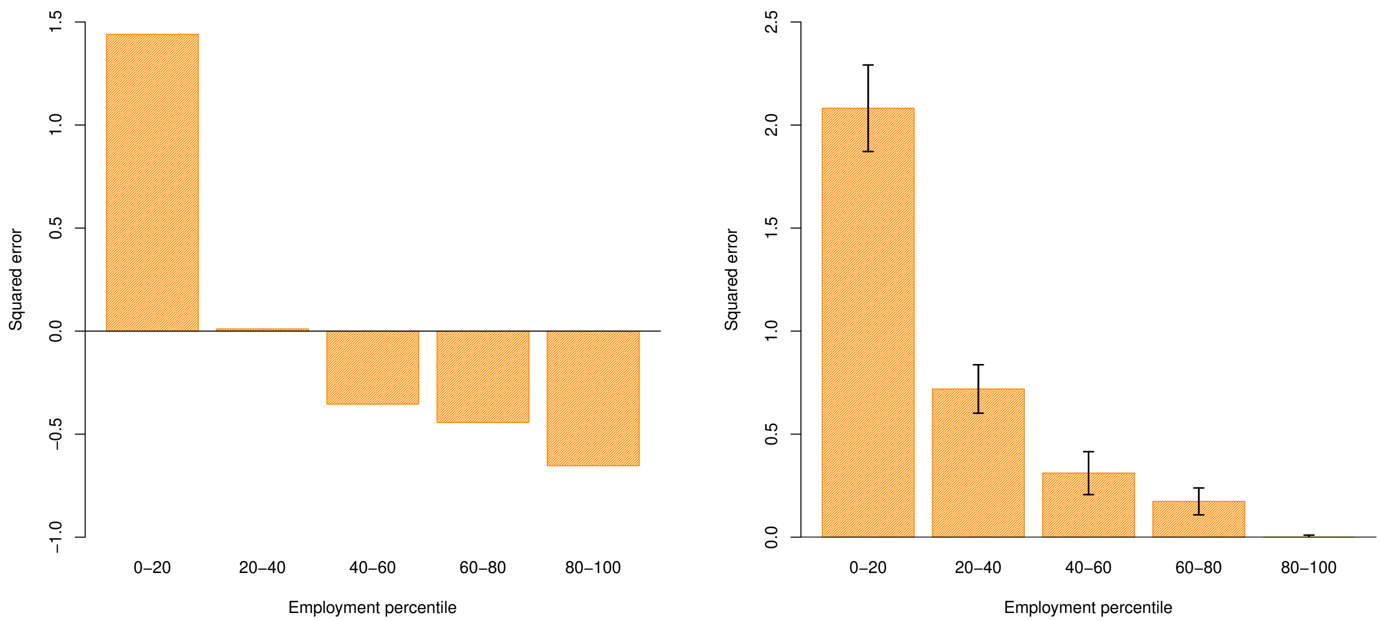


Panel (b): Size and time



Note: Data from the I/B/E/S-Compustat sample. Panel (a): the mean absolute error of one-year-ahead revenue forecasts on the left vertical axis, and the root mean-squared-error on the right axis. Revenue errors are scaled by a firm's tangible capital stock. Panel (b): the percentage increase from 2002 in the share of firms in a given year with employment exceeding the xth percentile of the 2002-employment distribution. The 50th, 80th, 90th percentile of the 2002-employment distribution correspond to around 1,000, 7,000, and 18,000 employees, respectively. Table A.3 in the Appendix shows the associated regression results.

Figure 2: Revenue Expectations Across the Size Distribution



Panel (a): Relative accuracy

Panel (b): Coefficient on size

Note: Panel (a) plots the difference between the squared error of one-year-ahead log-revenue forecasts from the I/B/E/S-Compustat merger within size (employment) quintiles and the overall average taken across all size levels. Panel (b) plots the coefficient estimates on size from a regression of the squared value of individual errors on the size quintile the firm belongs to, controlling for firm characteristics (Table I Column 3). Revenue errors are scaled by a firm's tangible capital stock and normalized by their mean value in the sample. Whisker-intervals are one-standard deviation robust (clustered) confidence bounds. Sample: 2002-2022.

taneously affect firm size and the accuracy of expectations. To address this issue, Panel (b) in Figure 2 plots estimates from a regression of the accuracy of firm expectations on firm-size, controlling for firm characteristics and time and sector fixed effects. Table I explores the effects of alternative controls and estimation methods, and crucially controls for changes in the volatility of revenue and productivity over time. Our results confirm the relationship in the raw data. The accuracy of expectations improves monotonically with size, even after controlling for characteristics: a larger firm, all else equal, produces more accurate forecasts.

Table A.5 in the Appendix shows that the documented accuracy-size relationship also extends to alternative data sets—in this case, The Duke-Richmond Fed CFO survey (Graham *et al.*, 2023; Appendix A.2)—which surveys firms' expectations of macroeconomic outcomes over which firms have no span of control. The latter is important as it further bolsters the case that accuracy improves with firm size due to improvements in information rather than merely differences in the predicted variable (i.e., revenues) across size.

The magnitude of the estimated effect of size in Table I are, moreover, considerable. Increasing the size of a firm by one quintile, for example, decreases the associated squared error by 47 percent of its average value (Column 1 in Table I). As documented in Panel (b) of Figure 1 and Table A.3-A.4 in the Appendix, over the past two decades, firm size has increased drastically—with, for example, a close to doubling in the share of firms with employment exceeding the 80th percentile of the 2002-employment distribution.[10] Crucially, after controlling for this evolution in the firm-size distribution, the effect of time itself becomes insignificant (Column 2 in Table I). This suggest that accuracy increases unrelated to firm size have played only a minor role over this period. Indeed, Figure A.2 in the Appendix, using estimates from Table I, shows that the change in the firm-size distribution alone can account for approximately 80 percent of the observed increase in forecast accuracy. With the addition of assets, as additional measures of size, this share increases to close to 85 percent. Clearly, these estimates cannot be interpreted as causal, as size and the accuracy of expectations are determined jointly (see e.g., Section 3). Yet, our results demonstrate that, over the past two decades, an intimate relationship has existed between firm size and the accuracy of firms' expectations.

We obtain similar estimates to those in Figure 1 and 2 for alternative measures of size and the accuracy of expectations. Table A.6 and Figure A.3 show similar estimates when proxying size with firm assets instead employment. Table A.7-A.8 documents that alternative measure of accuracy (e.g., the absolute error) likewise monotonically increase in size, irrespective of whether size is measured by employment or assets. We further find that across all-but-one sector accuracy has improved over time and increases with size (Figure A.4).

Table A.9-A.12 in the Appendix contain additional analysis and further robustness checks. We show that our findings extend to firm expectations of other variables than revenue (firm profits and capex expenditures), and to different transformation of firm revenue (e.g., percent revenue growth). We also show that the accuracy of firm expectations improves after large acquisitions of other firms (acquisitions that are at least 10 percent of firm assets), supporting the notion of a large fixed cost component to the processing of information, and extend to different assumptions about sectoral and time fixed effects. Finally, consistent with improvements in firm information driving the observed patterns in the micro data, Table A.12 documents that firms who have a larger stock of *acquired intangibles* (measured as in Chiavari and Goraya, 2023), which includes business software and expenditures on data processing, among others, report more accurate expectations.

In summary, the results in this section provide evidence for systematic heterogeneity in the accuracy of firm expectations—with pronounced consequences for the overall accuracy of firms' expectations. The rapid improvement in the accuracy of firms' expectations over the

[10]See also, e.g., Autor *et al.* (2020), Kwon *et al.* (2023), among others, and Appendix Figure A.1 for a version of Panel (b) in Figure 2 that uses the level of relative size.

Table I: Revenue Expectations, Firm Size, and Time

	Squared (log.) revenue errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm size	−0.468***	−0.454***		−0.416***	-0.286**	−0.430*
	(0.055)	(0.052)		(0.122)	(0.124)	(0.226)
Firm size (1)			2.082***			
			(0.210)			
Firm size (2)			0.719***			
			(0.118)			
Firm size (3)			0.311***			
			(0.104)			
Firm size (4)			0.174***			
			(0.065)			
Time		0.007				
		(0.007)				
Firm age		−0.063**	−0.072**	0.118**	0.184**	-0.117
		(0.032)	(0.033)	(0.057)	(0.067)	(0.093)
Log rev. volatility				-0.030		
				(0.027)		
Log TFP. volatility					0.907	
					(0.646)	
Observations	12,489	12,489	12,489	6,809	5,628	2,570
Sector FE	✓	✓	✓	×	×	×
Firm FE	×	×	×	✓	✓	✓
Time FE	×	×	✓	✓	✓	✓
Panel GMM	×	×	×	×	×	✓
F statistic	3.911***	3.922***	4.322***	9.295***	9.018***	NA.

Notes: Panel estimates from the merged I/B/E/S-Compustat sample. Column (1) shows estimates of the squared value of one-year-ahead log-revenue errors on firm size (employment) and sector (NAICS-4) fixed effects. Firm size is measured by the quintile the firm's employment is at time t relative to the 2002-employment distribution. Column (2) adds time and age controls. Column (3) allows for separate coefficients on size-levels (estimates are relative to the largest firms, those in the 80-100th percentile) and time fixed effects. Column (4) allows for firm fixed effects instead of sector fixed effects and controls for the individual four-year-rolling revenue volatility. Column (5) instead controls for individual four-year-rolling TFP volatility (Appendix A.2). Finally, Column (6) provides Arellano-Bond estimates. Revenue errors are scaled by firm capital and normalized by the overall average absolute (squared) error. The top and bottom 1 percent of errors have been removed. Robust (clustered) standard errors in parentheses. Sample: 2002-2022. *p<0.1,**p<0.05,***p<0.01

past two decades has been accompanied by a considerable increase in firm size, as larger firms produce more accurate forecasts. The data clearly reject the common-expectation assumption often used in full-information rational-expectation frameworks of firm behavior. Consistent with a shift in firms' information driving changes to the accuracy of firms' expectations, Appendix A.3 shows that firms which are more optimistic about future revenue also invest and employ more, and that more informed firms have more volatile input choices. We revisit the relationship between the accuracy of firms' expectations and firm-level outcomes in detail in Section 6.2. Motivated by the findings in this section, we next consider a canonical model of input allocation under uncertainty, which we enrich with information production by firms. We then use this framework to study the aggregate consequences of the rise in firm accuracy.

3 The Baseline Economy

We begin by developing our *baseline economy*, a central feature of which is that firms are uncertain about both *what to produce* as well as *how much to produce.*

3.1 Environment

Preferences, Endowments, and Technology. We consider an economy populated by a unit mass of households, indexed by $i \in [0,1]$, with CES-preferences over consumption:

$$\mathcal{U}_i = C_i = \left(\int_0^1 (\delta_{ij} \cdot c_{ij})^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}, \tag{1}$$

where c_{ij} is the household's consumption of variety $j \in [0,1]$, $\delta_{ij} \in \{\delta_H, \delta_L\}$ is the household's taste shifter with $\delta_H > \delta_L > 0$, and $\theta > 1$ is the elasticity of substitution across varieties. Each household is endowed with N units of labor, the economy's only factor of production.

The taste shifter δ_{ij} is distributed identically across households and independently across varieties. The share of δ_H-households for variety j, denoted by γ_j, is assumed to be random and to depend on what we refer to as *the type*, x_j, of the variety available in the market. Specifically, households may prefer either the red- or the blue-type variety, where $\omega_j \in \{\text{red}, \text{blue}\}$ denotes the *demand state* with $\mathbb{P}(\omega_j = \text{red}) = \mathbb{P}(\omega_j = \text{blue}) = \frac{1}{2}$. The households' demand for variety j is assumed to be higher when it is "customized to households' tastes":

$$\gamma_j = \gamma(x_j|\omega_j) \text{ where } \gamma(x_j = \omega_j|\omega_j) = \bar{\gamma} > \underline{\gamma} = \gamma(x_j \neq \omega_j|\omega_j) \quad \forall j,\ \omega_j.\text{[11]} \tag{2}$$

Each variety is produced by a monopolistically competitive firm, owned by the households.

[11] See Appendix B for a simple microfoundation of such consumer tastes.

Firm j chooses the type, x_j, of its variety at no cost, and produces the quantity y_j of it in accordance with the linear production technology:

$$y_j = A_j \cdot n_j, \tag{3}$$

where n_j are the units of labor employed by the firm and A_j denotes the firm's productivity.[12] Firm productivity is comprised of two components:

$$a_j \equiv \log(A_j) = \mu_j + \upsilon_j, \tag{4}$$

where $\mu_j \sim \mathcal{N}\left(0, \tau_\mu^{-1}\right)$ and $\upsilon_j \sim \mathcal{N}\left(0, \tau_a^{-1}\right)$ are distributed independently across firms and of each other, and where τ_μ^{-1} and τ_a^{-1} capture the dispersion in firm productivity.

Uncertainty and Information. A central friction in our economy is that firms are uncertain about their productivity and demand when making production choices. When choosing x_j and n_j, a firm knows its mean-productivity, μ_j, but it does not know the innovation to productivity, υ_j, nor the composition of its demand, ω_j.[13] As a result, the component μ_j is a source of *ex-ante heterogeneity* among firms, whereas υ_j and ω_j are sources of *ex-post uncertainty* that the firms may want to overcome through information production.[14]

A novel feature of our framework is that the firm can produce information to overcome its uncertainty about productivity and demand. In particular, the firm can obtain signals:

$$s_j^\upsilon = \upsilon_j + \varepsilon_j, \quad \varepsilon_j \sim \mathcal{N}\left(0, [\tau_j^\upsilon]^{-1}\right) \tag{5}$$

and

$$s_j^\omega \in \{\text{red}, \text{blue}\} \text{ with } \mathbb{P}\left(s_j^\omega = \omega_j | \omega_j\right) = \tau_j^\omega \in \left[\frac{1}{2}, 1\right], \tag{6}$$

where the errors of the signals are distributed independently of each other and of the errors of other firms' signals, and where $\tau_j^\upsilon \in \{\underline{\tau}^\upsilon, \bar{\tau}^\upsilon\}$ and $\tau_j^\omega \in \{\underline{\tau}^\omega, \bar{\tau}^\omega\}$ are the signal precisions.

We assume that, whereas the firm obtains the signals with precisions $(\underline{\tau}^\upsilon, \underline{\tau}^\omega)$ at no cost, it must allocate $\chi > 0$ units of labor to information production to increase the precisions of its signals to $(\bar{\tau}^\upsilon, \bar{\tau}^\omega) > (\underline{\tau}^\upsilon, \underline{\tau}^\omega)$. We denote firm j's information choice by $\iota_j \in \{0, 1\}$, where $\iota_j = 1$ whenever the firm produces information about its scale and product choice. To save on notation, in what follows, we let $\boldsymbol{s}_j \equiv \left[s_j^\upsilon,\, s_j^\omega\right]$ and $\boldsymbol{\tau}_j \equiv \left[\tau_j^\upsilon,\, \tau_j^\omega\right]$.

[12]Observe that the productivity, A_j, can equivalently be embedded into preferences by supposing that the taste shifter of consumer i for variety j is $A_j \cdot \delta_{ij}$ instead of δ_{ij}.

[13]In our baseline framework, knowing the realizations of υ_j and ω_j is sufficient for all of firm's decisions.

[14]Ex-ante heterogeneity is not essential for our results. It is, however, useful to "purify" potential mixed-strategy equilibria, and to better connect the theory to firm-level data. See Section 4 for further discussion.

3.2 Markets and Timing

Timing. The economy proceeds through three stages. In *Stage 1*, each firm j learns its mean-productivity level, μ_j, and chooses whether to produce information, ι_j. The economy then proceeds to *Stage 2*, where, conditional on its information choice, each firm observes its signals, $\boldsymbol{s}_j$, and decides the amount of labor to employ, n_j, and the type of variety to produce, x_j. The economy concludes in *Stage 3*, where each firm learns its productivity and demand states, (υ_j, ω_j), and produces; each household i, in turn, learns its tastes, $\{\delta_{ij}\}_j$, chooses its demand for each variety and supplies labor to firms; markets clear according to the protocols discussed next; and consumption takes place.

Markets. The market for labor is perfectly competitive: each household i supplies labor and each firm j hires the units of labor it desires to employ, taking the market wage, w, as given. In the market for variety j, each household takes its price, p_j, as given and chooses how many units of the variety to consume. By contrast, when choosing its production, the monopolistically competitive firm internalizes that its output affects the clearing price, p_j.

3.3 Remarks on Modeling Approach

In our baseline framework, information plays a dual role. First, the production of information helps a firm better learn its productivity state, υ_j, and hence choose its overall scale of production, i.e., learn *how much to produce*. This is a canonical approach to modeling information frictions at the firm level in macroeconomics, going back to at least Lucas (1972).

Second, the production of information also helps a firm better learn its demand state, ω_j, and hence allocate its factors towards the products most preferred by consumers, i.e., learn *what to produce*. Although we have modeled this channel through product customization, it is isomorphic to several natural alternatives: e.g., factor allocation choices between different plants, or input sourcing from different suppliers.[15] Common to all these interpretations is that the production of information helps a firm improve its internal factor allocation.

Combined, these two channels through which information affects firms are thought to have been among the most potent ways by which advancements in data-processing technologies have improved firm decision-making over the past two decades (Brynjolfsson and McElheran, 2016; Ali *et al.*, 2020; Mckinsey and Company., 2023; Veldkamp and Chung, 2024; Abis and Veldkamp, 2024). Yet, a common concern among academics and policymakers is that the advancements in data-processing technologies have also allowed firms to better discriminate and extract surplus from consumers. We will capture this third channel of information in Section 5, where the production of information will also help firms better learn *how to price* products.

[15] See, for example, the different business cases reported in O'Neill (2023).

As we will see, the interaction between all three channels will shape the normative properties of our economy, yielding valuable lessons about how to best regulate data production.

Finally, our baseline economy features both a fixed supply of production factors (i.e., labor) and a fixed set of firms or varieties. In Section 6, we show that standard approaches to introduce factor supply elasticity through capital accumulation and entry/exit of varieties simply amplify the aggregate effects of information production.

3.4 Optimization and Equilibrium

Household Problem. Household $i \in [0,1]$ chooses consumption of individual varieties $\{c_{ij}\}_{j\in[0,1]}$ to maximize its utility in (1) subject to the budget constraint:

$$\int_0^1 p_j \cdot c_{ij} \cdot dj = w \cdot N + \int_0^1 \pi_{ij} \cdot dj, \tag{7}$$

where p_j is the price of variety j, w is the wage, and π_{ij} are the profits from the firm producing variety j. The household takes prices, $\{p_j\}_{i\in[0,1]}$, and the wage rate, w, as given, when solving its problem. The solution yields:

$$c_{ij} = \delta_{ij}^{\theta-1} \cdot p_j^{-\theta} \cdot C_i, \tag{8}$$

where we have normalized the ideal price index to one. Since all households are ex-ante identical, $C_i = C$ for all i, and the aggregate demand for variety j is:

$$c_j \equiv \int_0^1 c_{ij} \cdot di = \delta_j^{\theta-1} \cdot p_j^{-\theta} \cdot C \quad \text{with} \quad \delta_j \equiv \delta(\gamma_j) = \left(\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot \delta_L^{\theta-1}\right)^{\frac{1}{\theta-1}}. \tag{9}$$

Thus, it is *as if*, for each variety j, there is a representative consumer with a demand shifter δ_j, which depends on the share γ_j of H-type consumers that the firm actually faces.

Firm Problem. The ex-post profits of firm $j \in [0,1]$ are given by the firm's revenue net of its expenditures on labor and information:

$$\pi_j = p_j \cdot y_j - w \cdot n_j - w \cdot \chi \cdot \iota_j. \tag{10}$$

In *Stage 2*, conditional on its information set $(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j)$, the firm chooses labor, n_j, and variety type, x_j, to maximize its expected profits from goods production:

$$\widehat{\pi}_j\left(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right) \equiv \max_{n_j,x_j} \mathbb{E}\left[p_j \cdot y_j - w \cdot n_j | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right], \tag{11}$$

subject to feasibility (3) and the output of the variety being equal its demand (9). Here,

$\mathbb{E}\left[\cdot|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]$ denotes the expectations operator conditional on $(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j)$. When choosing n_j, the firm optimally equates the expected marginal revenue product of labor to the wage:

$$\frac{\theta - 1}{\theta} \cdot \frac{\mathbb{E}\left[p_j \cdot y_j|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]}{n_j} = w. \tag{12}$$

When choosing the variety-type, the firm optimally sets:

$$x_j = \arg\max_{s_j^{\omega} \in \{\text{red,blue}\}} \mathbb{E}[p_j, y_j|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j]. \tag{13}$$

In *Stage 1*, conditional on its mean-productivity, μ_j, the firm chooses information production, ι_j, to maximize its expected profits. As a result, it optimally sets:

$$\iota_j \begin{cases} = 1 & \text{if } \mathbb{E}\left[\widehat{\pi}_j\left(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right)|\mu_j, \boldsymbol{\tau}_j = \bar{\boldsymbol{\tau}}\right] - w \cdot \chi \geq \mathbb{E}\left[\widehat{\pi}_j\left(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right)|\mu_j, \boldsymbol{\tau}_j = \underline{\boldsymbol{\tau}}\right] \\ = 0 & \text{otherwise} \end{cases}, \tag{14}$$

where $\mathbb{E}\left[\cdot|\mu_j, \boldsymbol{\tau}_j\right]$ denotes the expectations operator conditional on μ_j and $\boldsymbol{\tau}_j$.

Equilibrium Notion. An equilibrium of consists of allocations $\left\{\{c_{ij}\}_{i\in[0,1]}, y_j, n_j, x_j, \iota_j\right\}_{j\in[0,1]}$, prices $\{p_j\}_{j\in[0,1]}$, and wage w such that:

- Given the prices and the wage, the allocations solve the household and the firm problems, i.e., Equations (7)-(14) hold, and;
- Given the allocations, the goods and the labor markets clear, i.e., $c_j = y_j$ for all $j \in [0,1]$ and $\int_0^1 (n_j + \chi \cdot \iota_j) \cdot dj = N$.

4 Equilibrium Characterization

We proceed by studying cross-sectional outcomes at the firm level, taking as given all economy-wide variables (Section 4.1). We then turn to the aggregate consequences of firms' information choices (Section 4.2). We end this section by analyzing the aggregate effects of improvements in data-processing technologies within our baseline framework (Section 4.3).

4.1 Information in the Cross-Section

An advantage of the above framework is that firms' choices are driven by two simple objects. The first captures the relevant notion of *market size* faced by firms in our economy, and encodes all relevant general-equilibrium interactions. The second, by contrast, measures the profitability boost a firm can expect if it were to produce information.

The appropriate notion of market size is:

Definition 1. *Let* $\Omega \equiv C \cdot \left(\frac{\theta}{\theta-1} \cdot w\right)^{-\theta}$ *be the* ***market size*** *faced by firms in the economy.*

Thus, market size, Ω, is large when aggregate consumption demand, C, is large, or when labor costs, w, are low. Market size is a key determinant of firms' information production choices, in conjunction with what we refer to as firms' *information shifter*.

Definition 2. *For* $\boldsymbol{\tau} = (\tau_\upsilon, \tau_\omega)$*, define the firms'* ***information shifter*** *as:*

$$g(\boldsymbol{\tau}) \equiv \left[\tau_\omega \cdot \delta(\bar{\gamma})^{\frac{\theta-1}{\theta}} + (1-\tau_\omega) \cdot \delta(\underline{\gamma})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \cdot \exp^{\frac{1}{2} \cdot \frac{\theta-1}{\theta} \cdot \frac{1}{\tau_a} \cdot \frac{\tau_a + \theta \cdot \tau_\upsilon}{\tau_a + \tau_\upsilon}}, \tag{15}$$

where $\delta(\cdot)$ *is given by Equation (9).*

As we will see, $g(\cdot)$ compactly summarizes all the benefits that information has both at firm level and in the aggregate. We are now ready to characterize firms' optimal decisions.

Proposition 1. *In any equilibrium:*

(i) Firm j *with mean productivity* μ_j*, which observes signals* $\boldsymbol{s}_j$ *with precisions* $\boldsymbol{\tau}_j$*, chooses:*

$$x_j = s_j^\omega \quad \text{and} \quad n_j = \mathbb{E}\left[(\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^\theta \cdot \Omega. \tag{16}$$

(ii) Firm j *with mean productivity* μ_j *chooses:*

$$\iota_j = \begin{cases} 1 & \text{if} \quad \frac{1}{\theta-1} \cdot \left(\mathbb{E}\left[n_j | \mu_j, \boldsymbol{\tau}_j = \bar{\boldsymbol{\tau}}\right] - \mathbb{E}\left[n_j | \mu_j, \boldsymbol{\tau}_j = \underline{\boldsymbol{\tau}}\right]\right) \geq \chi \\ 0 & \text{otherwise} \end{cases}, \tag{17}$$

where:

$$\mathbb{E}\left[n_j | \mu_j, \boldsymbol{\tau}_j\right] = \exp^{(\theta-1) \cdot \mu_j} \cdot g(\boldsymbol{\tau}_j)^{\theta-1} \cdot \Omega. \tag{18}$$

Proposition 1 has two sets of important implications for firm behavior.

1) Information and Resource Allocation. Part (i) of Proposition 1 implies that information boosts the efficiency of resource allocation both *within* and *across firms*.

First, by helping a firm allocate its factors of production towards the variety-type most preferred by households, information increases firm-level total-factor productivity. To see this, observe that for given input and information choices (x_j, n_j, ι_j), the total surplus or utility generated by firm j rises monotonically with $(\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}}$.[16] Thus, an appropriate measure of

[16] The total surplus generated by firm j is equal to the total utility generated by the firm, $(\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}}$, net of its labor costs, $w \cdot (n_j + \chi \cdot \iota_j)$, all measured in the numeraire.

(log-)total factor productivity for firm j is:

$$\mathrm{tfp}_j \equiv \frac{\theta-1}{\theta} \cdot \log(\delta_j \cdot A_j) = \log(p_j \cdot y_j) - \frac{\theta-1}{\theta} \cdot \log(n_j) - \frac{1}{\theta} \cdot \log(C), \tag{19}$$

where the right-hand side follows from Equation (9) combined with market-clearing for variety j. Because the demand shifter, δ_j, faced by firm j is affected by the firm's choice of product customization, x_j, the distribution of tfp_j is endogenous to the firm's choice of information:

Corollary 1. *For all j, the conditional mean and variance of tfp is:*

$$\mathbb{E}[\mathrm{tfp}_j|\mu_j, \boldsymbol{\tau}_j] = \frac{\theta-1}{\theta} \cdot \left[\tau_j^{\omega} \cdot \log\left(\delta(\bar{\gamma})\right) + (1-\tau_j^{\omega}) \cdot \log\left(\delta(\underline{\gamma})\right) + \mu_j\right] \tag{20}$$

$$\mathbb{VAR}[\mathrm{tfp}_j|\mu_j, \boldsymbol{\tau}_j] = \left(\frac{\theta-1}{\theta}\right)^2 \cdot \left[\tau_j^{\omega} \cdot (1-\tau_j^{\omega}) \cdot \left[\log\left(\delta(\bar{\gamma})\right) - \log\left(\delta(\underline{\gamma})\right)\right]^2 + \frac{1}{\tau_a}\right], \tag{21}$$

where $\delta(\cdot)$ is given by Equation (9).

All else equal, tfp is higher and less volatile among firms with more precise demand information, i.e., a larger τ_j^{ω}. This is because firms with more precise demand information are able to customize their products more effectively to consumer tastes, thereby raising and stabilizing the effective demand for their products. We note that a variant of this "internal allocation" channel of information also appears in Farboodi and Veldkamp (2024), albeit modeled in reduced form that directly modifies the process for firm-level tfp.

Second, by helping a firm correlate its overall employment of production factors with the realized shocks to the firm's tfp, information also reduces (ex-post) factor misallocation across firms. To see this, let mrp_j denote the (*log-*)*marginal-revenue product* of labor for firm j:

$$\mathrm{mrp}_j \equiv \log(p_j \cdot y_j) - \log(n_j). \tag{22}$$

Absent information frictions, $\mathrm{mrp}_j = \mathrm{mrp}_{j'}$ for all j, j' (see Equation (12)). Any dispersion in mrp_j is thus a tell-tale sign of inefficiency resulting from information frictions.

Corollary 2. *For all j, the conditional variance of mrp is:*

$$\mathbb{VAR}[\mathrm{mrp}_j|\mu_j, \boldsymbol{\tau}_j] = \mathbb{VAR}[\mathrm{tfp}_j|\mu_j, \boldsymbol{\tau}_j] + \left(\frac{\theta-1}{\theta}\right)^2 \cdot \left(\frac{1}{\tau_a + \tau_j^{\upsilon}} - \frac{1}{\tau_a}\right) = \mathbb{VAR}[\mathrm{error}_j|\mu_j, \boldsymbol{\tau}_j], \tag{23}$$

where $\mathrm{error}_j \equiv \log(p_j \cdot y_j) - \log\left(\mathbb{E}[p_j \cdot y_j|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j]\right)$.

All else equal, factor misallocation is therefore lower among firms with more precise information, i.e., a larger τ_j^{υ} and τ_j^{ω}. This is because firms with more precise information are also those that have more accurate revenue forecasts. Indeed, the cross-sectional dispersion in mrp_j is equal to the variance of a firm's log-revenue forecast errors, a mapping we will later utilize to pin down the implied decline in mrp-dispersion from the observed increase in accuracy in the data (Section 2). We note that the role of information through its effect on factor misallocation has also been studied in David *et al.* (2016) and David and Venkateswaran (2019), albeit in a setting where firms do not themselves decide on their information production.

2) Information and Firm-size Distribution. Part (ii) of Proposition 1 implies that—by improving efficiency of resource allocation—information also alters the *firm-size distribution*.

To see this, consider the benefits to a firm from producing information, which are given by the change in the firm's expected profits from goods production resulting from a more efficient resource allocation (Corollaries 1 and 2). From the optimality condition (12), a firm's expected profits from goods production are proportional to its expected employment:

$$\mathbb{E}\left[p_j \cdot y_j - w \cdot n_j | \mu_j, \boldsymbol{\tau}_j\right] = \frac{1}{\theta - 1} \cdot w \cdot \mathbb{E}[n_j | \mu_j, \boldsymbol{\tau}_j]. \tag{24}$$

It then follows from Equation (18) in Proposition 1 that the information shifter $g(\cdot)$ is key to understanding the benefits of information. In particular, given the properties of $g(\cdot)$:

$$\frac{\partial \mathbb{E}[n_j|\mu_j, \boldsymbol{\tau}_j]}{\partial \tau_j^{\upsilon}} > 0, \;\; \frac{\partial \mathbb{E}[n_j|\mu_j, \boldsymbol{\tau}_j]}{\partial \tau_j^{\omega}} > 0, \;\; \frac{\partial^2 \mathbb{E}[n_j|\mu_j, \boldsymbol{\tau}_j]}{\partial \tau_j^{\upsilon} \partial \tau_j^{\omega}} > 0. \tag{25}$$

Thus, not only does each channel of information alone—whether learning about demand or productivity—boost a firm's size and profits, but the two channels interact and *reinforce* each other, amplifying the gains from information production.

We have so far shown that, holding fixed a firm's ex-ante mean productivity, μ_j, information production—by improving the efficiency of resource allocation—boosts that firm's expected size and profitability. In equilibrium, however, there is also a selection of firms into information production, which we must consider when studying any relationship between information and firm characteristics. Since the benefits from information production scale with a firm's expected size—which grows with μ_j (Equation 18),—but the information cost χ does not, it is the ex-ante more productive firms that choose to produce information. As it turns out, such a selection, if anything, reinforces the effects of information production that we outlined above.

Corollary 3. *In equilibrium, firm j produces information if and only if:*

$$\mu_j \geq \bar{\mu} \equiv \frac{1}{\theta - 1} \cdot \log\left[\frac{(\theta - 1) \cdot \chi}{\left(g\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} - g\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1}\right) \cdot \Omega}\right]. \tag{26}$$

Further, more informed firms, i.e., $\{j : \boldsymbol{\tau}_j = \bar{\boldsymbol{\tau}}\}$, have on average higher and less dispersed tfp, less dispersed mrp, and they grow larger and more profitable as measured by:

$$\mathbb{E}[X_j|\boldsymbol{\tau}_j = \bar{\boldsymbol{\tau}}] > \mathbb{E}[X_j|\boldsymbol{\tau}_j = \underline{\boldsymbol{\tau}}], \tag{27}$$

for $X_j \in \{n_j, n_j + \chi \cdot \iota_j, p_j \cdot y_j, p_j \cdot y_j - w \cdot n_j, \pi_j\}$.

To conclude, it is worth noting that, although in our setting selection into information production is driven by ex-ante productivity differences, alternative specifications are also possible. For example, the cross-sectional patterns described in Corollary 3 would be the same if we instead assumed that firms are heterogeneous in information costs (i.e., in χ_j); or if there was no heterogeneity whatsoever, but we instead focused on the parameter region where the equilibrium is in mixed strategies (i.e., where an interior share of firms produce information). Compared to these alternatives, our current approach, nevertheless, has the advantage of allowing us to more closely discipline the link between firm size and the accuracy of firms' information, using our empirical results documented in Section 2.

We have characterized how information production affects firm choices and outcomes at the micro level. The next natural step is to study our economy's general equilibrium. We return to validate the cross-sectional predictions, described in Corollaries 1-3 above, using the I/B/E/S-Compustat sample in Section 6.

4.2 Information in General Equilibrium

We begin by defining the relevant notion of *aggregate total factor productivity* (TFP) for our economy, which captures the units of aggregate consumption (or utility) our economy creates from the workers that it allocates to goods production.

Definition 3. *Given aggregate consumption, C, and aggregate employment in goods production, $\mathcal{N} \equiv \int_0^1 n_i \cdot di$, we define aggregate* ***total factor productivity*** *as $\mathcal{A} \equiv C \cdot \mathcal{N}^{-1}$.*

Using households' goods demands, market clearing for variety j, and firms' labor choices in Proposition 1, we can express TFP solely as a function of firms' information sets, $\{(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j)\}_j$, and hence their information choices:

$$\mathcal{A} = \left(\int_0^1 (\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}} \cdot \left(\frac{n_j}{\mathcal{N}}\right)^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}} = \left(\int_0^1 \mathbb{E}\left[(\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}} |\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj\right)^{\frac{1}{\theta-1}}, \tag{28}$$

where to obtain the last equality we have made use of the fact that:

$$\mathcal{N} = \int_0^1 \mathbb{E}\left[(\delta_j \cdot A_j)^{\frac{\theta-1}{\theta}} |\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj \cdot \Omega. \tag{29}$$

Since from Corollary 3, we know that firms' information choices are fully pinned down by the mean productivity $\bar{\mu}$ of the marginal firm that is just indifferent to producing information (henceforth, the *marginal-type*), we have that:

Lemma 1. *Given the marginal-type, $\bar{\mu}$, aggregate total factor productivity, $\mathcal{A}$, equals:*

$$\mathcal{A}\left(\bar{\mu}; g\right) \equiv \exp^{\frac{\theta-1}{2}\cdot\frac{1}{\tau_\mu}} \cdot \left[g(\underline{\boldsymbol{\tau}})^{\theta-1} \cdot (1-\xi(\bar{\mu})) + g(\bar{\boldsymbol{\tau}})^{\theta-1} \cdot \xi(\bar{\mu})\right]^{\frac{1}{\theta-1}}, \tag{30}$$

where $\xi(\bar{\mu}) \equiv \Phi\left(-\bar{\mu}\cdot\sqrt{\tau_\mu} + (\theta-1)\cdot\frac{1}{\sqrt{\tau_\mu}}\right)$ and $\Phi(\cdot)$ is the standard normal c.d.f.

The main implication of Lemma 1 is that, by boosting the efficiency of resource allocation—both within and across firms—information production raises the productivity of the economy as a whole. Notice that the weight $\xi(\bar{\mu})$ in Equation (30) captures the share of information producing firms in the economy, adjusted for the fact that these firms are larger (Corollary 3) and thus have a larger impact on the aggregate allocation of resources. As more firms produce information—that is, as $\bar{\mu}$ falls and $\xi(\bar{\mu})$ rises—more firms feature the larger information shifter and, as a result, TFP increases (since $g(\bar{\boldsymbol{\tau}}) > g(\underline{\boldsymbol{\tau}})$, see Definition 2). Note that we have made the dependence of TFP on the information shifter, g, explicit in Equation (30), a notational device that we will later utilize in Section 5.

Aggregate productivity is an important determinant of market size, $\Omega = C \cdot \left(\frac{\theta}{\theta-1}\cdot w\right)^{-\theta}$, and hence all economy-wide objects in our economy. Combining the definition of TFP with Equation (29) and the labor market-clearing condition shows that:

$$\Omega = \frac{\mathcal{A}(\bar{\mu}, g)\cdot\left[N - \Phi\left(-\bar{\mu}\cdot\sqrt{\tau_\mu}\right)\cdot\chi\right]}{\mathcal{A}(\bar{\mu}, g)^{\theta}}. \tag{31}$$

Recall from Section 4.1 that a firm's incentive to produce information depends on the market size, Ω. Equation (31) shows that, in general equilibrium, the market size itself also depends on the collective information choices of firms, as summarized by the marginal-type, $\bar{\mu}$.

Information production affects market size through its effect both on economy-wide consumption and on firms' production costs. First, the denominator in Equation (31) captures the fact that more information producers, i.e., a lower $\bar{\mu}$, raises firms' production costs, since by boosting TFP information also raises the demand for labor and hence the equilibrium wage ($w = \frac{\theta-1}{\theta}\cdot\mathcal{A}$). Second, the numerator in Equation (31), in part, captures the fact that more information production also raises aggregate consumption, as it raises the economy's TFP. Finally, the last term in the numerator shows that information production also has another depressing effect on overall consumption, as it diverts scarce labor away from the production of goods. It is straightforward to see that, since $\theta > 1$, the net effect of these opposing forces is negative, and market size decreases with information production (i.e., as $\bar{\mu}$ falls). This, in turn, implies that, in equilibrium, firms' information production choices are *strategic substitutes*, thereby guaranteeing the uniqueness of any equilibrium.

A convenient feature of our framework is that the economy's equilibrium can be studied through the intersection of just two schedules. Equation (31) defines a continuous schedule $\Omega : \mathbb{R} \to \mathbb{R}^{+}$, which maps a given marginal-type $\bar{\mu}$ into a market size $\Omega(\bar{\mu})$ that is consistent with market clearing. By contrast, Equation (26) defines a continuous schedule $\bar{\mu} : \mathbb{R}^{+} \to \mathbb{R}$ that for a given market size, Ω, yields the marginal-type $\bar{\mu}(\Omega)$ that is indifferent to producing information. An equilibrium is given by the fixed point of the composite map: $\bar{\mu} \circ \Omega : \mathbb{R} \to \mathbb{R}$. The following proposition states that such a fixed point exists and that it is unique.

Proposition 2. *An equilibrium exists, is unique, and in it the marginal-type that is just indifferent to producing information solves:*

$$\bar{\mu}(\Omega(\mu^{\star})) = \mu^{\star}, \tag{32}$$

where $\bar{\mu}(\cdot)$ *and* $\Omega(\cdot)$ *are defined by Equations* (26) *and* (31)*, respectively. Aggregate TFP and consumption are, in turn, given by:*

$$\mathcal{A}^{\star} = \mathcal{A}(\mu^{\star}, g) \text{ and } C^{\star} = \mathcal{A}^{\star} \cdot \left[N - \Phi\left(-\mu^{\star} \cdot \sqrt{\tau_{\mu}}\right) \cdot \chi\right], \tag{33}$$

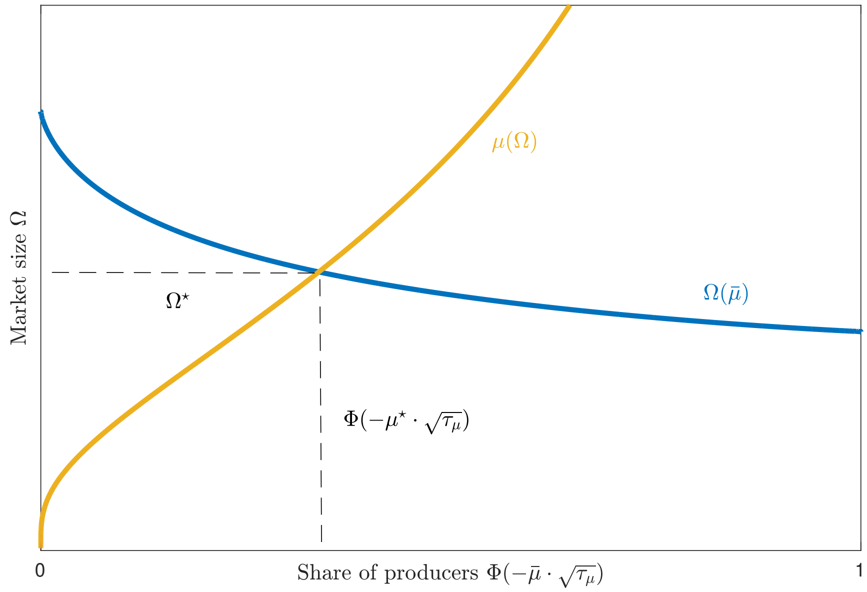
where $\mathcal{A}(\cdot)$ *is stated in Lemma 1 and* $\Phi(\cdot)$ *is the standard normal c.d.f.*

The equilibrium determination is illustrated in Figure 3, which depicts the equilibrium relationship between market size, Ω, and the share of information producers, as given by $\Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)$. The orange locus depicts the combinations of $\Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)$ and Ω that are consistent with the indifference condition in Equation (26). This locus is upward sloping because, as we discussed in Section 4.1, a firm's incentive to produce information increases with the market size. The blue locus, by contrast, depicts the combinations of $\Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)$ and Ω, which are consistent with market clearing, as described in Equation (31). As we discussed above, this locus is downward sloping. An equilibrium is characterized by the unique intersection of the orange and blue loci, which pins down the equilibrium marginal-type $\mu^{\star}$ and the market size $\Omega^{\star}$ corresponding to it.

4.3 On Advancements in Data-Processing Technologies

We now examine the macroeconomic consequences of advances in data-processing technologies using our baseline framework. The past two decades have seen firms increasingly adopt and rely on large-scale, data-intensive algorithms to enhance their economic decision-making (e.g.,

Figure 3: Equilibrium Determination



Note: The upward-sloping (orange) locus depicts the relationship between market size, Ω, and share of firms that produce information, $\Phi(-\bar{\mu} \cdot \sqrt{\tau_\mu})$, as defined by Equation (26). The downward-sloping (blue) locus instead depicts the relationship between Ω and $\Phi(-\bar{\mu} \cdot \sqrt{\tau_\mu})$ as defined by Equation (31).

Brynjolfsson and McElheran, 2016; Baley and Veldkamp, 2025). This shift in the nature by which firms make their economic choices has, in turn, been driven, in part, by substantial declines in computing costs and improvements in processing speeds (e.g., Nordhaus, 2008; Coyle and Hampton, 2024; Gill *et al.*, 2024).

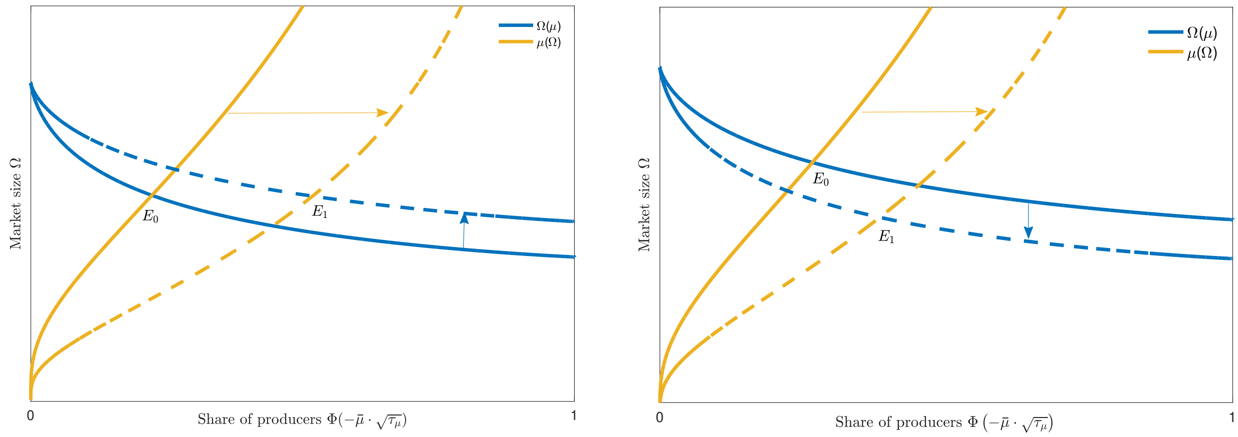
We analyze the aggregate effects of such technological advances through two comparative static exercises: (i) a reduction in the information cost parameter χ; and (ii) an increase in the precision of information that can be obtained through information production, $\bar{\boldsymbol{\tau}} = (\bar{\tau}_\upsilon, \bar{\tau}_\omega)$. These changes serve as stylized representations of declines in computing costs and improvements in processing capabilities. The following proposition summarizes their effects:

Proposition 3. *An improvement in data-processing technologies, such as a fall in χ, a rise in $\bar{\tau}_\upsilon$, or a rise in $\bar{\tau}_\omega$ leads to an increase in the share of firms producing information, $\Phi\left(-\mu^\star \cdot \sqrt{\tau_\mu}\right)$, and an increase in aggregate TFP, $\mathcal{A}^\star$, and welfare, $C^\star$.*

Figure 4 illustrates the equilibrium effects of changes in data-processing technologies on the share of information-producing firms, $\Phi(-\mu^\star \cdot \sqrt{\tau_\mu})$, and on the market size, $\Omega^\star$, respectively. Panel (a) depicts the impact of a decline in χ, while Panel (b) illustrates the consequences of an increase in $\bar{\boldsymbol{\tau}}$.[17] Both improvements make information production more attractive from a

[17]The aggregate effects of an increase in $\bar{\tau}_\upsilon$ are similar to those of an increase in $\bar{\tau}_\omega$.

Figure 4: Improvements in Data-Processing Technologies



Panel (a): a fall in χ Panel (b): a rise in $\bar{\boldsymbol{\tau}}$

Note: Panel (a) depicts the effects of a fall in the cost of information, χ, whereas Panel (b) depicts the effects of a rise increase in the accuracy of information, $\bar{\boldsymbol{\tau}} = (\bar{\tau}_\upsilon, \bar{\tau}_\omega)$. The solid (dashed) loci depicts the relationship between market size, Ω, and share of firms producing information, $\Phi(-\bar{\mu}\cdot\sqrt{\tau_\mu})$, before (after) the improvement in information technologies. Equilibria before (after) the change are denoted by E_0 (E_1).

firm's perspective (Proposition 1), leading to a rightward shift in the orange loci in Figure 4. However, their general equilibrium implications differ.

A reduction in χ shifts the blue locus upward, as lower information costs allow the economy to allocate more labor to goods production, thereby increasing consumption and expanding market size, $\Omega(\mu^\star)$. In contrast, an increase in $\bar{\boldsymbol{\tau}}$ shifts the blue locus downward, as the higher accuracy of firms' information enhances total factor productivity, which, as discussed in Section 4.2, has a depressing effect on the equilibrium market size, $\Omega(\mu^\star)$.

Despite these differing mechanisms, the overall macroeconomic effects of both technological improvements are, nevertheless, similar. In both cases, TFP, consumption, and welfare increase. This should not come as a surprise, however, given the benign nature of information assumed thus far. Indeed, we formally establish in Section 5.5 that the equilibrium of our baseline economy is efficient. As a result, in this setting, improvements in data-processing technologies are inherently beneficial, leading invariably to higher productivity and welfare.

5 The Rent-Extracting Economy

We have thus far taken a benign view of information, emphasizing its role in enhancing resource allocation within and across firms. Yet, the production and use of information need not be universally beneficial. A growing concern about recent advances in data-processing technologies is their potential to increase firms' capacity to extract consumer surplus by facilitating more sophisticated discriminatory practices (European Commission Report, 2020).[18] To examine this issue, we extend our baseline framework to analyze how information influences firms' pricing strategies. We refer to this extended framework as the *rent-extracting economy*, which, as we will show, encompasses our baseline economy as a special parametric case.

5.1 Information and Price Discrimination

Up to now, we have assumed that firms are restricted to sell varieties at unit (or linear) prices. However, given that each monopolistic firm faces consumers with heterogeneous tastes—i.e., a fraction $\gamma_j = \gamma(\omega_j|x_j)$ with demand-shifter δ_H and a fraction $1 - \gamma_j$ with demand-shifter δ_L—such a trading mechanism is generally sub-optimal.[19] We therefore now depart from the baseline framework by allowing each firm to design *the optimal trading mechanism* by which to allocate its goods to the different types of consumers. While we will effectively focus on *second-degree price discrimination through quantities*,[20] our qualitative results also hold in settings where price discrimination arises due to *bilateral bargaining* or *quality differentiation*. We refer the interested reader to Appendix C for these alternative specifications.

In what follows, we go through the main features of a firm's problem and relegate detailed derivations to Appendix C. The only change to our baseline setting of Section 3 is that, in *Stage 3*, each firm j now proposes a menu $\mathcal{M}_j = \{(t_j, q_j)\}$ to consumers, each of whom then decides whether and which allocation to accept. If the consumer accepts allocation (t_j, q_j), she receives q_j units of variety j in exchange for a payment of t_j; otherwise, she does not trade.

The firm's problem at this stage is to maximize its revenues:

$$\gamma_j \cdot t_j^H + (1 - \gamma_j) \cdot t_j^L, \tag{34}$$

where (t_j^l, q_j^l) denotes the allocation accepted by the type-$l \in \{H, L\}$ consumer.[21] This maximization problem is subject to incentive compatibility, individual rationality, and feasibility constraints. Since the firm does not observe individual consumer-types, in equilibrium, each consumer-type must select its intended allocation (*incentive compatibility*):

$$(t_j^l, q_j^l) = \arg \max_{(t_j, q_j) \in \mathcal{M}_j} (\delta_l \cdot q_j)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j \quad \text{for} \quad l \in \{H, L\}, \tag{35}$$

where the right-hand side of equation (35) is the total surplus that the consumer gains by

[18] See, e.g., O'Neill (2023) and Eeckhout and Veldkamp (2023).

[19] As it is trivial for the mechanism to elicit the common component, ω_j, of consumer preferences (see, e.g., Crémer and McLean (1988)), we assume without loss that the firm knows it when designing the mechanism.

[20] See, also, Bornstein and Peter (2024) for a recent macroeconomic application of discriminatory pricing.

[21] Recall that, at this stage, all costs are sunk. Revenue and profit maximization are, thus, equivalent.

accepting the allocation (t_j, q_j). Moreover, to participate in the mechanism, type-l consumer must obtain a non-negative surplus from it (*individual rationality*):

$$\left(\delta_l \cdot q_j^l\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j^l \geq 0 \quad \text{for} \quad l \in \{H, L\}. \tag{36}$$

Finally, as the firm supplies its variety inelastically in *Stage 3*, the aggregate quantity allocated to the consumers cannot exceed the quantity that the firm has produced (*feasibility*):

$$\gamma_j \cdot q_j^H + (1-\gamma_j) \cdot q_j^L \leq A_j \cdot n_j. \tag{37}$$

The solution to the firm's problem admits a standard form. At the optimum, the L-type's individual rationality, the H-type's incentive compatibility, and the feasibility constraints bind; in turn, the quantities allocated to consumers are set to equalize the marginal revenues extracted across types. It follows that the share of produced goods, α_j^l, that firm j allocates to each type-l consumer satisfies:

$$\alpha_j^H \equiv \alpha^H(\gamma_j) = \frac{\delta_H^{\theta-1}}{\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot (\psi_j \cdot \delta_L)^{\theta-1}}, \tag{38}$$

$$\alpha_j^L \equiv \alpha^L(\gamma_j) = \frac{(\psi_j \cdot \delta_L)^{\theta-1}}{\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot (\psi_j \cdot \delta_L)^{\theta-1}}, \tag{39}$$

where the sole departure from allocative efficiency is the "micro-level wedge":

$$\psi_j \equiv \psi(\gamma_j) = \begin{cases} \left[\frac{1-\gamma_j \cdot \left(\frac{\delta_H}{\delta_L}\right)^{\frac{\theta-1}{\theta}}}{1-\gamma_j}\right]^{\frac{\theta}{\theta-1}} & \text{if } \delta_L^{\frac{\theta-1}{\theta}} \geq \gamma_j \cdot \delta_H^{\frac{\theta-1}{\theta}} \\ 0 & \text{otherwise} \end{cases}, \tag{40}$$

which arises due to the binding incentive constraint of the H-type consumer.

The wedge $\psi_j \leq 1$ captures the fact that, to extract rents from the H-type more effectively, the firm chooses to inefficiently restrict trade with the L-type consumer. Indeed, at the optimum, the ratio of marginal utilities of consumption of the L-type to the H-type consumer equals $\psi_j^{-\frac{\theta-1}{\theta}}$, whereas efficiency requires equalization of marginal utilities. Moreover, since ψ_j decreases with γ_j, the departure from efficiency becomes even *larger* when the firm faces a *more favorable* selection of consumers, a feature that will be important in what follows.

5.2 Profit vs Social-Surplus Maximization

The upshot from the above concise characterization of the optimal mechanism is that firm j's ex-post profits, which govern the firm's optimal information and input choices in *Stages 1* and *2*, respectively, can be expressed as:

$$\pi_j = \left(\delta_j^R \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - w \cdot n_j - w \cdot \chi \cdot \iota_j, \tag{41}$$

where it is *as if* firm j faces a representative consumer with a "revenue-based demand shifter":

$$\delta_j^R \equiv \delta^R(\gamma_j) = \left(\gamma_j \cdot \left[\delta_H \cdot \alpha^H(\gamma_j)\right]^{\frac{\theta-1}{\theta}} + (1-\gamma_j) \cdot \left[\psi(\gamma_j) \cdot \delta_L \cdot \alpha^L(\gamma_j)\right]^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}. \tag{42}$$

By contrast, the social surplus produced by firm j is given by:

$$u_j = \left(\delta_j^S \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - w \cdot n_j - w \cdot \chi \cdot \iota_j, \tag{43}$$

where the "surplus-based demand shifter" that the firm faces equals:

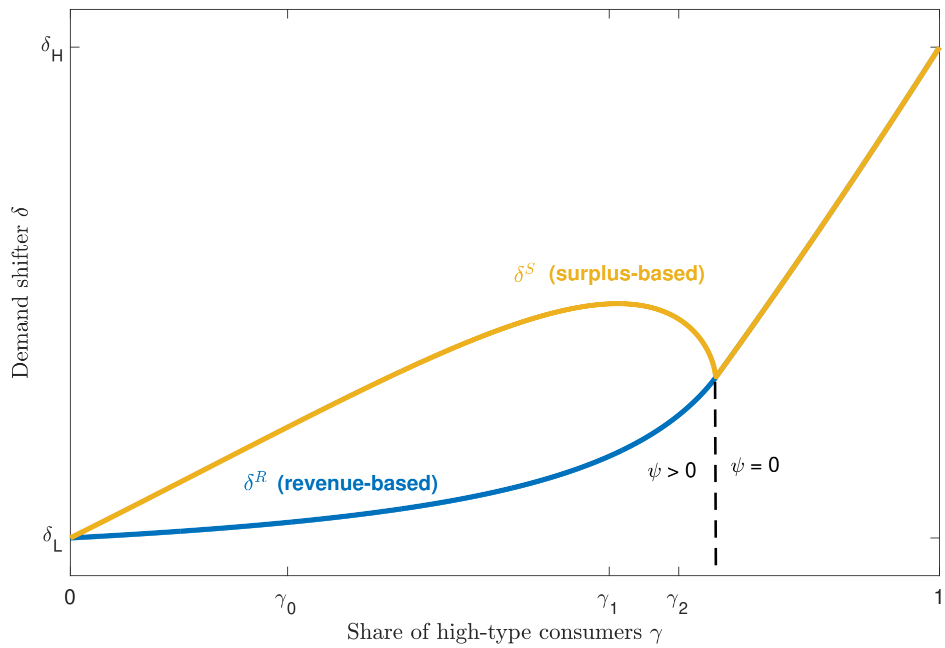
$$\delta_j^S \equiv \delta^S(\gamma_j) = \left(\gamma_j \cdot \left[\delta_H \cdot \alpha^H(\gamma_j)\right]^{\frac{\theta-1}{\theta}} + (1-\gamma_j) \cdot \left[\delta_L \cdot \alpha^L(\gamma_j)\right]^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}. \tag{44}$$

The properties of the demand shifters δ_j^R and δ_j^S, which we summarize next, will be central to understanding the workings of the rent-extracting economy. In particular, the difference between them will capture the conflict between profit and social surplus maximization that is inherent to the rent-extracting economy.

Lemma 2. *The revenue-based demand shifter, δ_j^R, is increasing in the share of high-demand types, γ_j, whereas the surplus-based demand shifter, δ_j^S, can be non-monotonic in γ_j. Moreover, $\delta_j^S \geq \delta_j^R$ with strict inequality if and only if $0 < \gamma_j < (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$.*

Figure 5 depicts these properties of the demand shifters δ_j^R and δ_j^S, as they depend on the share of H-type consumers. First, the revenue-based demand shifter, δ_j^R, increases monotonically in γ_j, since the firm can always extract a larger surplus from consumers when their willingness to pay for the product increases. Second, the difference between the two demand shifters captures the information rents that the firm must leave to the H-type consumer to satisfy incentive compatibility. As a result, this difference is positive whenever there is a positive mass of H-types and the firm allocates some units of the good to the L-types—i.e., when $0 < \gamma_j < (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$. An immediate implication of these properties is that the ratio of the two demand shifters, δ_j^S/δ_j^R, must *increase at first* and *then decrease* with γ_j. Moreover, as the

Figure 5: Revenue- vs Surplus-Based Demand Shifters



Note: The figure depicts the demand shifters $\delta^R(\gamma_j)$ and $\delta^S(\gamma_j)$ as a function of γ_j. In the figure, rent extraction is mild if $\underline{\gamma} = \gamma_0 < \gamma_1 = \bar{\gamma}$, whereas it is both severe and socially destructive if $\underline{\gamma} = \gamma_1 < \gamma_2 = \bar{\gamma}$.

figure shows, the departure from allocative efficiency—as captured by the ratio of marginal utilities across the two types of consumers (see earlier discussion)—can be so severe that the surplus-based demand shifter, δ_j^S, can actually *decrease* with γ_j. For reasons that will become apparent soon, it is useful to distinguish between these different scenarios.

Definition 4. *We say rent extraction is* ***severe*** *(**mild**) if δ_j^S/δ_j^R falls (rises) as γ_j increases from $\underline{\gamma}$ to $\bar{\gamma}$, and it is* ***socially destructive*** *if δ_j^S falls as γ_j increases from $\underline{\gamma}$ to $\bar{\gamma}$.*

Intuitively, recall that by producing information and customizing its products more effectively, a firm raises the likelihood that it faces a share $\bar{\gamma}$ (rather than $\underline{\gamma}$) of H-type consumers from $\underline{\tau}^\omega$ to $\bar{\tau}^\omega$. Hence, when rent extraction is severe (mild), the social return to information about demand is lower (higher) than the private return; when rent extraction is socially destructive, the social return to information about demand is instead negative. These implications of price discrimination will be key for the results that follow. In Appendix C, moreover, we show that similar implications also obtain in alternative, plausible trading environments, where discrimination occurs through bilateral bargaining or quality differentiation.

5.3 Equilibrium of The Rent-Extracting Economy

We are ready to characterize the equilibrium of the rent-extracting economy. To do so, we define two key objects. First, we introduce a modified version of the information shifter, which will be instrumental in describing firm-level choices and outcomes:

$$g^R(\boldsymbol{\tau}) \equiv \left[\tau^\omega \cdot \delta^R(\bar{\gamma})^{\frac{\theta-1}{\theta}} + (1-\tau^\omega) \cdot \delta^R(\underline{\gamma})^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} \cdot \exp^{\frac{1}{2}\cdot\frac{\theta-1}{\theta}\cdot\frac{1}{\tau_a}\cdot\frac{\tau_a+\theta\cdot\tau^\upsilon}{\tau_a+\tau^\upsilon}}, \tag{45}$$

where we substitute the demand shifter δ_j in Equation (15) with the revenue-based demand shifter, δ_j^R, as defined in Equation (42). As before, $g^R(\bar{\boldsymbol{\tau}})$ increases in both components of $\bar{\boldsymbol{\tau}}$.

Second, we define a measure of the misalignment between profit and social surplus maximization for a firm with information precision $\boldsymbol{\tau} = (\tau^\upsilon, \tau^\omega)$:

$$\Delta(\boldsymbol{\tau}) \equiv \left[\frac{\tau^\omega \cdot \delta^S(\bar{\gamma})^{\frac{\theta-1}{\theta}} + (1-\tau^\omega) \cdot \delta^S(\underline{\gamma})^{\frac{\theta-1}{\theta}}}{\tau^\omega \cdot \delta^R(\bar{\gamma})^{\frac{\theta-1}{\theta}} + (1-\tau^\omega) \cdot \delta^R(\underline{\gamma})^{\frac{\theta-1}{\theta}}}\right]^{\frac{\theta}{\theta-1}}. \tag{46}$$

Crucially, this misalignment measure decreases (increases) with information precision τ^ω whenever rent extraction is severe (mild), as formalized in Definition 4.

With these definitions in place, we now analyze firm-level choices and outcomes:

Proposition 4. *An equilibrium of the rent-extracting economy exists, is unique, and in it:*

(i) Firm j's choices of x_j, n_j and ι_j are given by Proposition 1, with the only modification that the demand-shifter δ_j in Equation (16) is replaced by δ_j^R.

(ii) The equilibrium marginal-type, $\mu^\star$, is given by Proposition 2, with the only modification that the information shifter $g(\cdot)$ in Equations (26) and (31) is replaced by $g^R(\cdot)$.

Thus, when it comes to choices of product-type, x_j, employment, n_j, and information production, ι_j, the behavior of firms in the rent-extracting economy is observationally equivalent to that in our baseline economy.[22] This should not come as a surprise: the only difference in the revenues and profits, associated with those choices, arises because firms now act as if facing the demand shifter δ_j^R, as opposed to δ_j. It then follows directly that the amount of information produced in the aggregate, as before, is pinned down by the unique fixed point of the composite map $\bar{\mu} \circ \Omega$, with the only difference that the schedules $\bar{\mu}(\cdot)$ and $\Omega(\cdot)$, defined in Equations (26) and (31), now use the modified information shifter $g^R(\cdot)$ in place of $g(\cdot)$.

[22]Formally, all other parameters fixed, there is a continuum of rent-extracting economies indexed by $(\delta_L, \delta_H, \underline{\gamma}, \bar{\gamma})$, which coincide in firm-level choices $\{(x_j, n_j, \iota_j)\}_j$ and revenues $\{p_j \cdot y_j\}_j$. This continuum includes, in particular, the economy without asymmetric information, i.e., $0 = \underline{\gamma} < \bar{\gamma} = 1$.

An immediate consequence of Proposition 4 is that by looking only at *firm-level data* one cannot distinguish the rent-extracting economy from our baseline economy. The cross-sectional predictions, as described in Corollary 3, also hold for firms in the rent-extracting economy: namely, when measured using revenue data, more informed firms have higher and less volatile productivity (tfp), less dispersed marginal revenue products of inputs (mrp), and they grow larger and more profitable. There is, nevertheless, an important caveat. Since in the rent-extracting economy there is a conflict between profit and social surplus maximization, revenue-based measures of tfp and factor misallocation can provide misleading information about the efficiency of resource allocation. This, in turn, implies that—in the aggregate—the rent-extracting economy behaves very differently from our baseline economy.

We can express the aggregate TFP of the rent-extracting economy as:

$$\mathcal{A} = C \cdot \mathcal{N}^{-1} = \frac{\left(\int_0^1 \Delta(\boldsymbol{\tau}_j)^{\frac{\theta-1}{\theta}} \cdot \mathbb{E}\left[(\delta_j^R \cdot A_j)^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 \mathbb{E}\left[(\delta_j^R \cdot A_j)^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj}, \tag{47}$$

where $\Delta(\boldsymbol{\tau}_j)$ is the misalignment measure defined in Equation (46). We observe two differences compared to the expression for TFP of our baseline economy in Equation (28). First, as we have already discussed, firm choices reflect the revenue-based demand shifter δ_j^R as opposed to the original demand shifter δ_j, in Equation (9). Second, the part of the social surplus that firms fail to capture from consumers still enters into aggregate consumption, and it is captured by the misalignment measure $\Delta(\boldsymbol{\tau}_j)$ present in the numerator. As the next proposition shows, both departures alter the aggregate behavior of the rent-extracting economy:

Proposition 5. *Let $\mu^\star$ be the marginal type that is indifferent to producing information in equilibrium. Aggregate TFP and consumption in the rent-extracting economy are given by:*

$$\mathcal{A}^\star = \mathcal{E}\left(\mu^\star\right) \cdot \mathcal{A}(\mu^\star, g^R) \quad and \quad C^\star = \mathcal{A}^\star \cdot \left[N - \Phi\left(-\mu^\star \cdot \sqrt{\tau_\mu}\right) \cdot \chi\right], \tag{48}$$

in which the "macro-level wedge" satisfies:

$$\mathcal{E}(\mu^\star) \equiv \left[\Delta(\underline{\boldsymbol{\tau}})^{\frac{\theta-1}{\theta}} \cdot (1 - \zeta(\mu^\star)) + \Delta(\bar{\boldsymbol{\tau}})^{\frac{\theta-1}{\theta}} \cdot \zeta(\mu^\star)\right]^{\frac{\theta}{\theta-1}}, \tag{49}$$

where $\zeta(\mu^\star) \equiv \frac{g^R(\bar{\boldsymbol{\tau}})^{\theta-1} \cdot \xi(\mu^\star)}{g^R(\underline{\boldsymbol{\tau}})^{\theta-1} \cdot (1-\xi(\mu^\star)) + g^R(\bar{\boldsymbol{\tau}})^{\theta-1} \cdot \xi(\mu^\star)} \in (0,1)$ is decreasing in $\mu^\star$, $\mathcal{A}(\cdot)$ and $\xi(\cdot)$ are defined in Lemma 1, and $g^R(\cdot)$ and $\Delta(\cdot)$ are defined by Equations (45) and (46), respectively.

Proposition 5 reveals that aggregate TFP and welfare in the rent-extracting economy are affected by the macro-level wedge, $\mathcal{E}(\mu^\star)$, which is the aggregate counterpart to the firm-level measure of misalignment between profit and social surplus maximization.[23] In the special case where firms are perfectly informed about consumer preferences—i.e., when $0 = \underline{\gamma}$ and $\bar{\gamma} = 1$—this misalignment disappears: $g^R(\cdot) = g(\cdot)$ and $\mathcal{E}(\cdot) = 1$. The equilibrium then mirrors that of the baseline economy. However, in more general cases, the macro-wedge $\mathcal{E}(\mu^\star)$ captures a pecuniary externality that emerges in equilibrium due to firms' rent-extracting behavior. Each firm makes its information, input, and pricing choices to maximize its private rent extraction from consumers. Yet, when all firms engage in such behavior, it becomes detrimental to the welfare of all consumers—who, as the ultimate owners of the firms, would otherwise benefit from a more efficient allocation of resources.

We will show shortly that this pecuniary externality creates inefficiencies and provides a rationale for corrective policy interventions. Before turning to policy, however, we establish a paradoxical result that highlights the inefficiencies embedded in the laissez-faire equilibrium of the rent-extracting economy.

5.4 Improvements in Data-Processing: Redux

Advances in data-processing technologies—such as a reduction in the cost parameter χ or a rise in the precision $\bar{\tau}^\omega$—alter firms' ability to extract rents from consumers. As a result, these technological improvements have countervailing effects. This is in contrast to our baseline economy, in which advances in information processing were unambiguously beneficial.

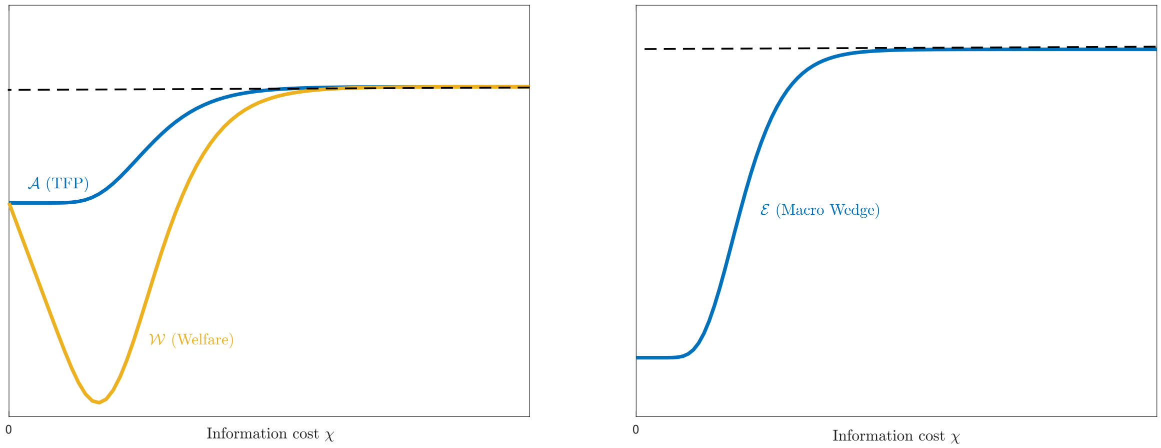
Corollary 4. *An improvement in data-processing technologies, such as a fall in χ, or a rise in $\bar{\tau}^\omega$, leads to an increase in the share of information producers, $\Phi(-\mu^\star \cdot \sqrt{\tau_\mu})$, but has ambiguous effects on the aggregate TFP, $\mathcal{A}^\star$, and welfare, $C^\star$.*

The counterintuitive nature of this result can be understood through two concrete examples. First, consider the case in which firms have complete information about consumer preferences—that is, $\underline{\gamma} = 0$ and $\bar{\gamma} = 1$. As discussed earlier, in this situation, the allocations of the rent-extracting economy coincide with those of our baseline economy. Consequently, improvements in information-processing technologies—whether through reductions in χ or increases in $\bar{\tau}^\omega$—necessarily increase both TFP and welfare (Proposition 3).

Now, consider a different scenario in which information production provides little additional information about productivity, i.e., $\bar{\tau}^v \approx \underline{\tau}^v$. Suppose that the cost of information, χ, falls from a prohibitively high level to zero, under conditions where price discrimination is *socially destructive*, i.e., $\delta^S(\bar{\gamma}) < \delta^S(\underline{\gamma})$ (Definition 4). In this setting, the misalignment is more pronounced among information-producing firms—i.e., $\Delta(\bar{\boldsymbol{\tau}}) < \Delta(\underline{\boldsymbol{\tau}})$—leading to a decline in

[23] For instance, as $\mu^\star \to -\infty$ and all firms produce information, $\mathcal{E}(\mu^\star) \to \Delta(\bar{\boldsymbol{\tau}})$; instead, as $\mu^\star \to +\infty$ and no firm produces information, $\mathcal{E}(\mu^\star) \to \Delta(\underline{\boldsymbol{\tau}})$.

Figure 6: Socially Destructive Improvements in Data-Processing Technologies



Note: The figure depicts the aggregate TFP, consumption and the macro-level wedge, as they depend on the information cost χ, for the parametric case when rent-extraction is socially destructive (see Definition 4).

the macro-level wedge, $\mathcal{E}$, as shown in Figure 6. As a result, the rise in the share of H-type consumers reduces overall social surplus, causing TFP and welfare to decline despite the fall in χ (Figure 6).[24] Furthermore, in this same scenario, a rise in $\bar{\tau}^{\omega}$ from a value close to $\underline{\tau}^{\omega}$ to a higher level can be shown to produce qualitatively similar effects to the decline in χ. These findings suggest that improvements in data-processing technologies can sometimes exacerbate inefficiencies from rent-extracting behavior, leading to potential welfare losses.

5.5 Optimal Corrective Regulation

We now study the normative properties of the economy. We consider the problem of a benevolent social planner who maximizes aggregate welfare, $\int_i \mathcal{U}_i di$, by making optimal production and consumption choices, $\{x_j, n_j, \iota_j\}_j$ and $\{c_{ij}\}_{ij}$. The planner operates under the same technological and informational constraints as agents in the decentralized economy. For each j, the timing of the planner's choices is as follows. In *Stage 1*, the planner chooses information production, ι_j, conditional on μ_j. In *Stage 2*, she chooses the variety-type, x_j, and employment, n_j, conditional on $(\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j)$. In *Stage 3*, the planner designs the mechanism to allocate consumption, (c_{Hj}, c_{Lj}), conditional on $(\mu_j, \upsilon_j, \omega_j)$.[25] These choices are subject to the resource constraints: $\int_j (n_j + \chi \cdot \iota_j) \cdot dj \leq N$ and $\gamma_j \cdot c_{Hj} + (1 - \gamma_j) \cdot c_{Lj} \leq A_j \cdot n_j$ for all j.

We say that the decentralized equilibrium is *efficient* if its allocations coincide with those of the planner; otherwise, it is *inefficient*. We next state our first normative result:

[24] Indeed, TFP is equal to $b \cdot \delta^S(\underline{\gamma})$ before the fall in χ, for some constant $b > 0$, and it declines to $b \cdot \delta^S(\bar{\gamma})$ after the fall. Since $C^\star = \mathcal{A}^\star \cdot N$ before and after the fall in χ, changes in consumption track changes in TFP.

[25] This is a problem in mechanism design, as in Section 5.1, except the planner's objective is social surplus, rather than profit, maximization.

Proposition 6. *The social planner's allocations coincide with those of our baseline economy. Hence, the laissez-faire equilibrium of the rent-extracting economy is generically inefficient.*

Proposition 6 establishes two key results. First, that the equilibrium of our baseline economy is efficient. This result aligns with the well-established normative properties of CES economies in the tradition of Dixit and Stiglitz (1977). It is well known that when factors of production are inelastic, such economies generally achieve efficiency despite the presence of market power. Importantly, the additional features of our framework—information production and preference heterogeneity—do not alter this fundamental property.

Second, a direct implication of Proposition 6 is that the inefficiency of the rent-extracting economy stems from the misalignment between profit maximization and social surplus maximization (Section 5.2). Indeed, if firms were to design trading mechanisms with the objective of maximizing social surplus rather than profits, the resulting allocations would coincide with those of the baseline economy and, thus, be efficient.[26]

Overall, Proposition 6 serves as a useful normative benchmark. Yet, it also underscores a practical challenge in achieving the efficient outcome. Implementing this outcome may require *direct* policy interventions in firms' pricing strategies—an approach that may be difficult to implement in practice. Rather than pursuing such interventions, we focus below on more constrained and arguably more realistic policies. In particular, we explore interventions that target firms' information choices, which we broadly refer to as *data-regulation policies*.

Data-Regulation Policies. We now suppose that the only instrument at the planner's disposal is a tax $w \cdot T$ on information production, with proceeds rebated lump-sum to households. Under this intervention, the only modification to the equilibrium conditions is in the determination of the marginal type $\mu^\star$ for a given market size, Ω: firms now face an information cost (in units of labor) of $\chi + T$ rather than χ. Consequently, choosing T is equivalent to directly selecting $\mu^\star$. The next proposition characterizes the properties of optimal interventions.

Proposition 7. *The optimal tax, T, is positive (negative) if rent extraction is severe (mild).*

A simple perturbation argument helps illustrate this result. Consider a small change in the tax leading to a marginal shift in information production, $d\mu^\star$. Aggregate consumption and welfare are affected through two channels (Proposition 5):

- A change in the macro-wedge, $\mathcal{E}'(\mu^\star) \cdot d\mu^\star$.
- A change in residual welfare, $\frac{d\left(\mathcal{A}(\bar{\mu}, g^R) \cdot \left[N - \Phi(-\bar{\mu} \cdot \sqrt{\tau_\mu}) \cdot \chi\right]\right)}{d\bar{\mu}}\Big|_{\bar{\mu}=\mu^\star} \cdot d\mu^\star$.

[26]Note that efficiency would generally not be attained by forcing firms to post unit prices. When the economy's factor supply is elastic, such a policy would simply replace distortions due to rent-extraction with more conventional distortions due to monopolistic markups.

In equilibrium, the latter effect is fully internalized by firms and is thus zero. The change in the macro-wedge then captures the non-internalized welfare effects of information production:

$$\frac{dC^\star}{C^\star} = \frac{\mathcal{E}'(\mu^\star)}{\mathcal{E}(\mu^\star)}. \tag{50}$$

Thus, information production is excessive (insufficient) whenever $\mathcal{E}'(\cdot) > 0$ ($\mathcal{E}'(\cdot) < 0$), which holds if rent extraction is *severe (mild)*, as formalized in Definition 4.

When $\mathcal{E}'(\cdot) > 0$, by producing information and—through product customization—effectively raising the share of H-type consumers they face, firms extract consumer surplus at a faster pace than they contribute to social welfare, leading to excessive information production. The optimal tax, therefore, discourages firms from information production. However, a simple information tax may be too blunt an instrument. When rent extraction is so severe as to be *socially destructive* (Definition 4)—a conflict arises: information production provides firms with both socially valuable information (about productivity, υ_j) and socially harmful information (about demand, ω_j).[27] A more refined policy addresses this conflict better.

Let us next suppose that, in addition to the information tax, the planner can also "garble" the signals received by firms. Formally, suppose the planner increases the noise in the signals obtained through information production from $(\bar{\tau}^\upsilon, \bar{\tau}^\omega)$ to:

$$(z^\upsilon \cdot \underline{\tau}^\upsilon + (1 - z^\upsilon) \cdot \bar{\tau}^\upsilon, z^\omega \cdot \underline{\tau}^\omega + (1 - z^\omega) \cdot \bar{\tau}^\omega), \tag{51}$$

where $z^\upsilon, z^\omega \in [0, 1]$ are policy parameters chosen by the planner. Notably, if given the choice, firms would never garble their own signals. Consequently, $(\bar{\tau}^\upsilon, \bar{\tau}^\omega)$ can be interpreted as the technological upper bounds on data-processing capabilities. While regulatory interventions cannot expand this technological frontier, they can limit firms' ability to exploit it. The following proposition demonstrates that a more targeted garbling policy is preferable when information about productivity and demand have conflicting effects on social surplus.

Proposition 8. *The planner never garbles information about productivity but garbles information about demand if rent extraction is socially destructive, i.e., in the case where* $\delta^S(\bar{\gamma}) < \delta^S(\underline{\gamma})$*, in which case* $z^\omega = 1$ *and* $T = 0$*.*

Intuitively, when information about demand is socially harmful, a policy of garbling signals about demand increases the macro-wedge, $\mathcal{E}$, to its upper bound, $\delta^S(\underline{\gamma})/\delta^R(\underline{\gamma})$. Once the planner sets $z^\omega = 1$, $\mathcal{E}$ becomes independent of information production, i.e., of $\mu^\star$. As seen in Equation (50), firms then internalize the social surplus generated by their information choices.

[27] Note that the fact that the socially valuable information takes the form of signals about productivity is merely due to our modeling choices. As discussed in footnote 12, an isomorphic reformulation of our model replaces information about firm productivity with information about shocks to consumer preferences.

Broader Policy Lessons. The data-regulation policies outlined above offer valuable insights into the ongoing policy debates surrounding firms' access to and use of consumer data. A central concern among regulators is that unrestricted access to consumer data may enable firms to misuse personal information, potentially engaging in discriminatory practices without consumer awareness. In response, the European Union's General Data Protection Regulation (GDPR) includes provisions aimed at curbing firms' ability to collect, store, and exploit consumer data in manners that may foster discriminatory behavior.[28]

Although stylized, the interventions of Propositions 7 and 8 support the general aims of such regulatory measures, while also highlighting critical caveats. First, as demonstrated in Proposition 7, the optimal regulation of data may involve *subsidizing* information production. This is because rent extraction is not always socially harmful. Indeed, it may incentivize firms to internalize a greater share of the social surplus generated through their choices, raising overall welfare. Second, as shown in Proposition 8, even when rent extraction is socially harmful, blanket restrictions on information production are an overly blunt instrument. In fact, regulatory measures that broadly limit access to consumer data are not optimal, and policies that selectively target socially harmful information sources are preferable.

Finally, while the preceding analysis focused on interventions targeting the economy's information structure—a logical approach given the central role of information frictions in equilibrium inefficiencies—a natural question arises: could more elaborate policies yield better outcomes? The answer is "yes". In Appendix C, we investigate richer policies, which allow the social planner to target the externality more effectively by making data regulation also size dependent. Although these policies are firm-specific, making implementation more complex, we show they exhibit key parallels to the aforementioned data-regulation policies.

An instructive case arises in the scenario in which rent extraction is severe, so that optimal data regulation reduces firms' incentives to produce information by imposing a tax (Proposition 7). We show that a more targeted policy—besides achieving this objective—also reduces the firm-size concentration. This is because, in this scenario, in the laissez-faire equilibrium, large firms are excessively large relative to the size that is warranted by their contribution to social surplus. This result contrasts sharply with the findings from the literature that explores the welfare costs of rising market power (e.g., Edmond *et al.*, 2023; Boar and Midrigan, 2024; Eeckhout *et al.*, 2024). A common theme in this work is that large firms—those that have higher market power and markups—are inefficiently small, precisely because they constrain production to raise prices. By contrast, in our rent-extracting economy, firms do not need to constrain production to extract consumer surplus, as they can do so through price discrimination instead. As a consequence, we find that large firms are indeed *too large*.

[28] See https://gdpr.eu/ for details on the General Data Protection Regulation in the European Union.

6 Supporting Evidence and Quantification

We have so far shown how advances in data-processing technologies affect the economy by enabling firms to better determine (i) how much to produce, (ii) what to produce, and (iii) how to price their products. Our results indicate that advances in data-processing can be either beneficial or detrimental to economic efficiency and welfare. Yet, our analysis has so far also remained silent on the broader trends and their decomposition over the past two decades. Has the documented increase in firm information, as presented in Section 2, contributed to higher overall productivity and welfare? And, if so, by how much and through which channels? To address these questions, we proceed to calibrate and quantify our baseline and rent-extraction economies using our data and results from Section 2.

6.1 Model Validation and Parametrization

Before we use our model framework as a quantitative laboratory, we provide a first-pass validation of our theory. We document that the cross-sectional predictions of our model are both qualitatively and quantitatively consistent with salient features of US firm-level data.[29]

Qualitative Validation: We begin by qualitatively validating the cross-sectional predictions of our framework, discussed in detail in Section 4.1 and summarized in Corollary 3.

1) Information and Resource Allocation: First, one role of information within our framework is that it helps improve input allocation *within* a firm. Indeed, (revenue-based) measured tfp is, all else equal, higher and less volatile for more informed firms, as firms with more precise demand information are better able to customize products, thereby raising and stabilizing the effective demand for them. Consistent with this prediction, Panel (a) in Figure D.1 documents a pronounced negative relationship between a firm's squared revenue error and a firm's tfp, even after controlling for firm age and sector. In the data, as in the model, a more accurate firms is, all else equal, more productive.[30] Figure D.3 further confirms that a more accurate firm also has a lower volatility of measured tfp.

Second, by helping a firm correlate its inputs with the realized shocks to the firm's tfp, information also reduces (ex-post) factor misallocation *across* firms. Panel (b) in Figure D.1 reports the average cross-sectional dispersion in the *marginal-revenue product* of labor in the data (mrpn), where we report estimates separately for accurate and inaccurate firms. We define "an informed firm" as one that (i) is below the median in terms of the mean-squared-

[29] Recall that the baseline economy and the rent-extracting economy are observationally equivalent when using data on firm-level revenues and input choices (see Proposition 4 and footnote 22).

[30] Recall that we estimate (revenue-based) firm-level tfp as in Ottonello and Winberry (2020), but amend the approach to be consistent with a finite elasticity of substitution. Our approach is consistent with an extension of our framework that allows for capital in production (see also Section **??**).

error of one-year-ahead revenue expectations; and (ii) one for which we have at least two observations. Appendix D.1 discusses details behind the computation. The panel also reports estimates of misallocation based on the marginal revenue product of capital and total factor revenue productivity (mrpk and tfpr), respectively. Across the three different measures of sectoral misallocation, more informed firms exhibit less cross-sectional dispersion, consistent with more informed firms being better able to better predict their productivity and demand.[31] Clearly, differences in distortions unrelated to accuracy may account for a bulk of the discrepancy (e.g., David and Venkateswaran, 2019). Nevertheless, on balance, the evidence in Panel (b) points towards systematic improvements in resource allocation across firms as the accuracy of firms' expectations is enhanced.

2) Information and Firm-size Distribution: Another central consequence that information has in our framework is on firm size. In line with our motivating evidence, discussed in Section 2 (Figure 2), it is, all else equal, larger firms that choose produce information. Yet, as we have discussed, the production of information itself causes a firm to expand in size, as information improve the efficiency of resource allocation. Our framework, therefore, features a close, two-sided relationship between the accuracy of a firm's information and the firm's size. Figure A.12 in the Appendix utilizes the panel dimension of our data set to show that, consistent with our framework, more informed firms at time t also grow faster over time.

In summary, the main cross-sectional predictions of our theory, highlighted in Corollary 3, are *qualitatively* consistent with firm-level outcomes. We next turn to the *quantitative* match between model and data with a special focus on the two-sided relationship between the accuracy of expectations and firm size. This requires us to first parameterize our framework.

Model Calibration: The aim of our parametrization is to ensure that our baseline model and its extension can quantitatively account for salient features of firm-level outcomes and capture the rich heterogeneity in expectations documented. To do so, we set the elasticity of substitution between goods, θ, equal to 3 (Hsieh and Klenow, 2009), normalize the labor endowment, N, equal to 1, and calibrate the rest of the parameters internally. We focus for concreteness on the rent-extracting economy, absent asymmetric information between firms and consumers, i.e., $\bar{\gamma} = 0 < 1 = \underline{\gamma} = 1$. As we have already discussed, firm-level outcomes in this economy coincide both with those of our baseline economy and with those of a continuum of rent-extracting economies, in which there is asymmetric information, i.e., $0 < \bar{\gamma}$ or $\underline{\gamma} < 1$. This economy provides the most benign view of information, since by construction it features no conflict between rent extraction and surplus maximization by firms. We set the variance

[31] The striking difference of around 30-40 percent in cross-sectional dispersion visible in Panel (b) in Figure D.1 is robust to alternative definitions of "accurate and inaccurate" (e.g., focusing on firms in the top quartile of the error distribution instead), sectoral definitions (e.g., considering six-digit NAICS industries), as well as a consistent feature across time.

Table II: Parametrization: model vs. data (2002-2007)

	Data	Model
Mean of log-productivity of informed firms	0.033	0.037
Mean of log-productivity of uninformed firms	0.015	0.015
Variance of log-productivity of informed firms	0.058	0.056
Variance of log-productivity of uninformed firms	0.108	0.131
Unconditional variance of log-productivity	0.097	0.123
Root-mean-squared error of informed firms	0.036	0.036
Root-mean-squared error of uninformed firms	0.132	0.132
Share of information producing firms	0.100	0.100

Note: The table compares data moments from I/B/E/S-Compustat sample over the period 2002-2007 to those from the calibrated model. The table shows the mean and variance of log-productivity, in addition to the root-mean-squared-error of firms' one-year-ahead log-revenue forecasts. Firm productivity is estimated as in Ottonello and Winberry (2020). We define an informed firm as a firm that is in the bottom 10 percent of the mean-squared-error distribution over the initial period and for which we have at least four observations.

of *ex-ante* log-productivity, τ_μ^{-1}, the variance of productivity shocks, $(\tau^v)^{-1}$, and the posited symmetric demand shifters, $\delta_H = \exp(\widehat{\delta})$ and $\delta_L = \exp(-\widehat{\delta})$, to match the unconditional variance of log-productivity over the first five years of our sample (2002-2007).[32] We also use the latter parameters to match the conditional variance of *informed* and *uninformed* firms' productivity over this period. We conservatively assume that 10 percent of firms are informed initially, consistent with the evidence in Brynjolfsson and McElheran (2016) on the share of firms that use data-driven decision-making towards the end of our initial period (2002-2007).[33] We calibrate the information cost parameter, χ , to target this value. Finally, we set the precision of firms' information, $\underline{\boldsymbol{\tau}}$ and $\bar{\boldsymbol{\tau}}$, to match the mean-squared-error of informed and uninformed firms' revenue expectations. Table II shows the match between model moments and data. Table D.1 in the Appendix summarizes the parameter estimates.

Quantitative Validation: A central implication of our theory is a close relationship between firms' information production choices and firms' size. In the above, we have already explored the *qualitative* match between the data and our model on this dimension. We now leverage our calibrated model to *quantitatively* confront our framework with the motivating evidence discussed in Section 2. To do so, we simulate expectation errors from the calibrated model over a 20-year period, where we linearly decrease the information cost, χ, to match the 41 percent increase in average accuracy, documented earlier. We also linearly increase $\bar{\boldsymbol{\tau}}$ to match the developments in revenue accuracy and in the volatility of productivity for information-producing firms. We set the number of observations per firm per year to that in the data.

[32]The assumption that taste shifters are symmetric is a normalization, since the overall level of demand for a firm's product is not relevant for our identification strategy and quantitative results.

[33]We define an informed firm as one that is in the bottom 10% of the squared-error distribution.

Table III: Size and Accuracy Relationship

	log. squared errors	
	Data	Model
Size (labor)	-0.454^{***}	-0.480^{***}
	(0.052)	(0.001)
Time (years)	0.007	-0.089^{***}
	(0.007)	(0.002)

Note: Least-squares estimates of the relationship between squared normalized errors and firm size (quintiles of the initial employment distribution). We estimate this relationship both in the I/B/E/S-Compustat data and in the calibrated model (Section 2). The column labelled data further controls for sector fixed effects and age (Column (2) in Table I). Robust (clustered) standard errors in parentheses. *p<0.1,**p<0.05,***p<0.01.

Table III and Figure D.3 show how firms' information choices in equilibrium translate into a monotone relationship between the accuracy of firm expectations and firm size.[34]

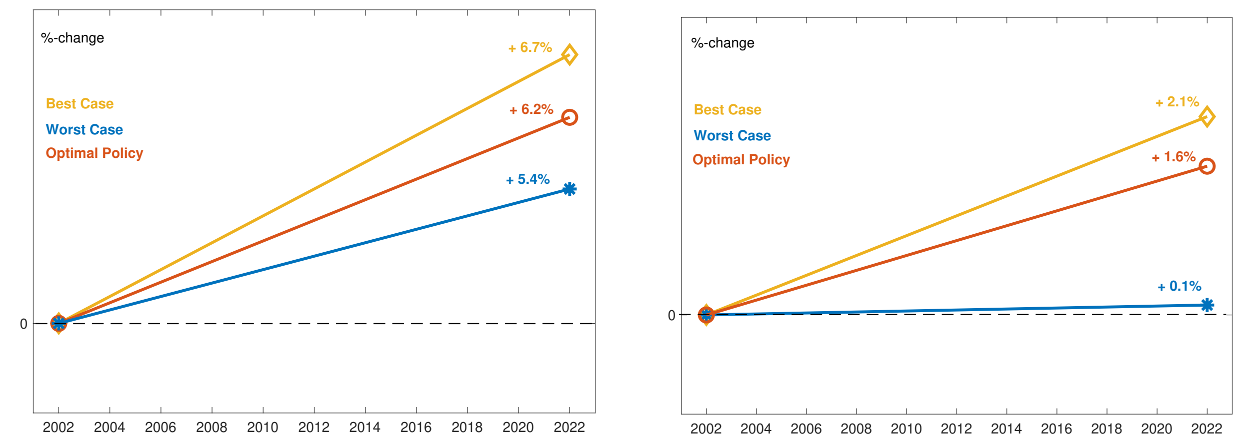
Although our calibration does not explicitly target the size-accuracy relationship, the model generates a size-accuracy relationship which closely resembles that in the data. The regression coefficient on size, measured by a firm's employment quintile, is -0.480 in the model and -0.454 in the data (Table III). In the model, as in the data, increasing the size of a firm by one quintile decreases the associated squared error by 45-50 percent of its average value. The model, furthermore, matches the slope of the size-accuracy relationship decently well (Figure D.3), although the model entails too large an improvement in expectations when transitioning from the fourth to the fifth quintile relative to that in the data.

Crucially, our calibrated model also matches salient features of the evolution in data-use and firm size over time. Precise estimates of firms' use of data-processing technologies over time are notoriously difficult to come by (Baley and Veldkamp, 2025). That said, a recent study by Brynjolfsson and McElheran (2024) puts the share of medium-to-large manufacturing firms who systematically use data to inform their decision-making in 2021 at around 73%. The model slightly undershoots this quantity and predicts a share of information-producing firms at the end of 2022 closer to 72%. But the rise is remarkably similar for such a reductionist model. Lastly, the model also exhibits a rise in the share of employment by large firms over our sample period, although the model slightly exaggerates this change: the share of overall employment attributed to firms above the 80th percentile of the employment distribution has, e.g., risen by 15pp. in the model and around 6-7pp in the data.

In summary, the results in the previous subsections have shown that our framework both

[34] To match the data, we estimate that the cost of information production, χ, has fallen by 42%, while the high-accuracy of productivity and demand information, $\bar{\tau}^{\upsilon}$, and $\bar{\tau}^{\omega}$, has increased by 10% and 2%, respectively.

Figure 7: Effects of Improvements in Data-Processing Technologies



Panel (a): TFP

Panel (b): Welfare

Note: Panel (a) shows the estimated effects for different calibrated models on TFP, $\mathcal{A}$. Panel (b) depicts the results for overall welfare, $\mathcal{C}$. We showcase results for the "best-case" scenario, i.e., the model with $\underline{\gamma} = 0$ and $\bar{\gamma} = 1$, and for the "worst-case" scenario, which is estimated to $\underline{\gamma} = 0.71$ and $\bar{\gamma} = 0.87$. We also illustrate the results for the "worst-case" scenario under the optimal corrective policy described in Section 5.5.

qualitatively and *quantitatively* captures salient relationships between the accuracy of firms' expectations and firm-level outcomes. We conclude that our model provides a suitable laboratory to explore the consequences that the evolution in firm accuracy has on the macroeconomy.

6.2 Quantification and Decomposition

We compute the economy-wide effects of decreasing the information cost, χ, to match the 41 percent increase in average accuracy over our sample period, documented in Section 2. We also linearly increase $\bar{\boldsymbol{\tau}}$ to match the developments in revenue accuracy and in the volatility of productivity for information-producing firms. Because of the indeterminacy linked to firm pricing, we compute our results in two cases: We search over all combinations of $\{\hat{\delta}, \underline{\gamma}, \bar{\gamma}\}$ that yield the same revenue-based demand shifters, and hence provide us with the same model moments , and choose the highest and lowest welfare parametrization. We refer to these two cases as the "best" and "worst-case" economy, respectively, and they help provide bounds for the overall effects of improvements in data-processing on the economy. As previously discussed, the "best case" economy corresponds the rent-extracting economy in which there is no uncertainty about consumer types ($\underline{\gamma} = 0, \bar{\gamma} = 1$). This economy also yields identical outcomes to our baseline economy. Figure 7 and Table IV summarizes our results.

On balance, the consequences of improvement in data-processing on economy-wide productivity are considerable. Over the past two decades, TFP improvements are estimated to be in the ballpark of 5.4%-6.7% (Panel (a) in Figure 7). This compares with a 15% increase in TFP over our sample period in the data.[35] The estimated effects, furthermore, account for close to 2/3rds of the overall increase in TFP possible from removing information frictions. We compute the later estimates by setting the cost information production to zero and increasing the accuracy towards infinity and one, for tfp and demand-side information, respectively. We then re-compute relevant variables in the economy without information frictions and compare our results.[36] Although, there are clear uncertainties related to our estimates, taken at face value, our results simultaneously suggest that (*i*) improvements in firms' data-use has been a large contributor to the rise in overall TFP over the past two decades; and (*ii*) that most of the overall TFP improvement has already been accounted for.

Table IV decomposes the overall rise in TFP into its three constituent channels, discussed above, highlighting a main advantage of our framework—that it allows for an exact decomposition of the overall effect. The table shows that the largest contributor by far to the rise in TFP is firms' decreased uncertainty about their optimal scale of operation. This channel alone comprises more than 3/4 of the overall rise in TFP. By contrast, the capacity to better match products to consumer tastes is estimated to have only increased TFP by around 1.6pp over our sample period. Indeed, in the worst-case economy, the benefits from improved product design are almost entirely eaten up by firms' improved ability to extract rents from consumers, leading to further misallocation, which we estimate to be at most 1.5pp.

Although the overall rise in TFP is reasonably similar for the best-case (6.7%) and worst-case (5.3%) scenario, we estimate the welfare consequences of the improvements in data-processing technologies to be more starkly different. Panel (b) in Figure 7 shows that, under our best-case scenario, economy-wide welfare has increased by around 2.1% as a result of advances in data-processing. By contrast, under our worst-case scenario, the entirety of these welfare benefits are instead eaten up by firms' increased ability to extract rents from consumers. As such, the worst-case scenario estimates that there has been almost no welfare benefits from advances in data-processing over the past two decades.

Clearly, the worst-case scenario may overstate the detrimental consequences from rent extraction that we find. Notwithstanding this possibility, our results do, nevertheless, show that a stark disconnect is quantitatively possible between the improvements in TFP that follow from data-processing technologies and the potential welfare effects that they have once one internalizes the resulting changes in how firms also set prices.

This disconnect, in turn, raises the question of the potential welfare improvements that

[35] See, e.g., the FRED series on TFP (`https://fred.stlouisfed.org/series/RTFPNAUSA632NRUG`).

[36] The increase in TFP from removing information frictions is 6.5% and 8.9% in the two cases.

Table IV: Decomposition of The Rise in TFP

Model	Overall (%)	Scale (pp)	Product (pp)	Pricing (pp)	$\underline{\gamma}$	$\bar{\gamma}$
Best case	6.7	5.1	1.6	0	0.00	1.00
Worst case	5.3	5.1	1.6	-1.5	0.71	0.87

Note: The table decomposes the rise in TFP in Figure 7 into its three constituent channels: (i) scale, (ii) product design, and (iii) pricing. The table does so for the "best case" and for the "worst case" economy.

corrective policy can achieve. Table IV shows that, in the worst-case scenario, the economy operates in the "severe rent-extraction". region of the parameter space. As a result, an optimal tax or revenue subsidy can improve welfare. Panel (b) in Figure 7 illustrates that the optimal corrective subsidy, discussed in Section 5.5 and Appendix C, in this case, indeed can increase the welfare gains from 0.1% to 1.6%. Put differently, we estimate that 1.5pp of the potential welfare benefits are eaten up by excessive information production by firms. As such, at the end of our sample period, we estimate that the optimal data-regulation lowers the share of information producers by 5pp (to 67% instead of 72%). Consistent with this more limited increase in the share of information producers, the optimal policy also halves the rise in the share of employment by large firms relative to the no-policy counterpart.

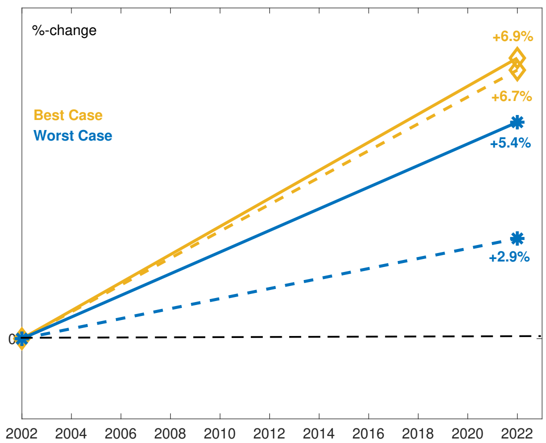
6.3 Extended Quantification: Capital and Variety Accumulation

A worry one might have about the above estimates is that they provide a "conservative" range. The rent-extracting economy features both a fixed supply of production factors (i.e., labor) and a fixed set of varieties of goods, both of which, in turn, limit the scope for the production of information to influence economy-wide outcomes. To explore the consequences of data-processing advancements in environments that are less rigid, we augment the rent-extracting economy with capital and variety accumulation. Appendix D.6 discusses and summarizes the extended model. We focus in what follows, for simplicity, on the steady-state of the extended economy. Figure 8 contrasts the results from improvements in data-processing technologies to those highlighted in Figure 7, using the same calibration strategy.[37]

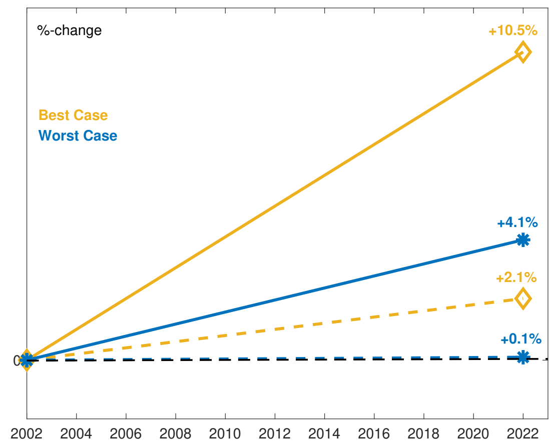
Compared to the earlier estimates, the range between the best- and worst-case scenarios now increases. Although the estimate for the overall rise in TFP in the best-case scenario is only modestly larger than before (6.9% instead of 6.7%), the rise under the worst-case scenario

[37] In the extended model, we estimate that the cost of information production, χ, has fallen by 33%, while the upper-accuracy parameters, $\bar{\tau}^{\nu}$ and $\bar{\tau}^{\omega}$, have increased by 10% and 2%, respectively. We discuss the calibration of the extended model in Appendix D.6.2. Notice that the fall in the information cost, χ, is smaller than before; this follows the increased "elasticity" of the extended to increases in information production.

Figure 8: Extended Quantification



Panel (a): TFP



Panel (b): Welfare

Note: Panel (a) shows the estimated effects for different calibrated models on TFP, $\mathcal{A}$. Solid lines indicate results for the extended quantification, while dashed lines indicate those from Figure 7. Panel (b) instead depicts the results for overall welfare, C. We showcase results for the "best-case" scenario, i.e., the model with $\underline{\gamma} = 0$ and $\bar{\gamma} = 1$, and for the "worst-case" scenario in each case.

is smaller (2.9% instead of 5.4%). As Table D.2 in the Appendix shows, the main reason for this discrepancy is a modest increase in the TFP drag caused by rent-extraction combined with the decumulation of varieties in the equilibrium of the economy. The latter, due to the well-known "love-of-variety" effect, decreases TFP. By contrast, the scale and product channels are of similar magnitudes to before. At its heart, the reason for the decumulation of varieties, and the lower increase in TFP, in the worst-case scenario is that the increased rent-extraction, which follows from the increase in information production, lowers TFP. This, in turn, decreases market size in the economy, making it less attractive for new firms to enter, leading to further decreases in TFP and market size over time. In this sense, the decumulation of varieties amplifies the negative TFP effects that rent-extraction has in our framework.

Finally, notwithstanding that the notion of welfare is complicated in the extended model, as any transition towards a new steady-state could take time, Figure 8 shows that the estimated increase in steady-state consumption (welfare) is now larger. This arises because of the capacity of the economy to accumulate factors of production (i.e., capital), increasing the consumption rise in response to advancements in data-processing technologies. Crucially, however, a sizable gap between the best- and worst-case scenario remain, highlighting once more the potential benefits that corrective data-policy can have.

In summary, in this section, we have used our baseline and rent-extracting economies as quantitative laboratories to provide bounds on the possible economy-wide consequences of advancements in data-processing technologies. Calibrating our model to developments in our firm-level dataset, we estimate that data-processing advancements have significantly increased TFP over the past two decades (c. 3.0-7.0%), primarily by helping better firms determine their optimal scale of operation (c. leading to a 5pp increase in TFP). Yet, the welfare benefits of these advancements can appear modest—and are often in the range of only a couple of percent. The main reason for the potential lackluster welfare benefits is the increased ability of firms to extract rents from consumers, which, in turn, stresses the potential benefits from optimal corrective policy.

7 Conclusion

Advances in data-processing technologies have the potential to transform most aspects of economic life. In this paper, we have focused on a particular facet of the ongoing data revolution: its capacity to improve the accuracy of firms' information about economic fundamentals. Using micro data on managerial forecasts, we have documented a systematic increase in the accuracy of US firms' expectations over the past two decades, and shown that this increase is tightly tied to changes in the firm-size distribution. To explore the macroeconomic consequences of these developments, we have proposed a quantitative-theoretical framework, where information enables firms to optimize their *scale*, *product choice*, and *pricing strategies*.

Consistent with our estimates, our model shows that firms that use information more intensely allocate inputs more efficiently, adopt more preferred products, are more profitable, and grow faster and larger. We have illustrated the macroeconomic consequences of the these shifts in firm performance. For plausible parameter values, consistent with the observed increase in firm accuracy, our main estimates document that TFP (household welfare) would have been 5.3-6.7% (0.1-2.1%) lower in 2022 absent the increase in the accuracy of US firms. We have further decomposed this overall estimate into its constituent channels. On balance, we find that the lion's share of the rise in TFP (c. 2/3-3/4) arises due to improvements in firms' capacity to better determine their optimal scale with improvements in product design playing distinct secondary role. Nevertheless, we also estimate that most of the welfare benefits from this rise in TFP may have been eaten up by excessive information production by firms. Our findings, thus, highlight a potential central role for data-regulation in insuring that advances in data-processing technologies indeed result in economy-wide welfare improvements.

Finally, beyond the analysis in this paper, we see important scope for extending our framework to also account for how advances in data-processing technologies alter the way in which households search over which goods to purchase. Another avenue for future research is to exploit product-level data for a large share of the overall economy to provide sharper bounds on the potential consumer costs of advances in data-processing technologies than those provided above. In this paper, we have taken a first pass at this issue using firm-level data.

A Motivating Evidence

A.1 Data Construction: I/B/E/S-Compustat

In our main analysis of firms' forecasts, we use a combination of the I/B/E/S managerial guidance database and Compustat Fundamentals Annual. The combined sample for the I/B/E/S-Compustat merger covers the period 2002-2022 for 12,917 firm-years spanning 2,570 US firms. To construct our sample, we follow convention and discard utilities and financials, as well as any firm-years that have negative or non-existing values for revenue, employment, and/or the capital stock. We focus on revenue forecasts, which comprise the lion-share of all forecasts provided by managers, and analyze one-year ahead annual forecasts.[38] We only use "centered forecasts": that is, either point estimates or forecasts that are stated as a range. In the latter case, we use the mid-point of the range as the point estimate. We remove observations that are related to the top and bottom 1 percent of the forecast error distribution.

Variable Definitions: We use the following variables from Compustat Fundamentals Annual: revenue (code: `sale`), profits (code: `ib`), capital (code: `ppent, ppegt`), investment (code: `capx`), assets (code: `at`), employment (code: `emp`), mergers and acquisitions (code: aqa), and industry classification (code: `naics` and `sic`). We measure a firm's debt as the total net value of liabilities (code: `dllt+dlc-che`) and the stock of acquired intangibles, adjusted for amortization and finanical goodwill as, as in Chiavari and Goraya (2023) (code: `ITAN+AM-GDWL`). We deflate nominal variables where appropriate with US CPI (code: `CPIAUCLS` from FRED) and compute (revenue-based) total factor productivity as in Ottonello and Winberry (2020). Finally, Compustat only has limited data on wages. We use total labor and related expenses as our measure of the overall wage bill (code: `xlr`). We link the Compustat data with the I/B/E/S database using the CRSP ID that is available for both. The annual forecasts employed from the I/B/E/S managerial guidance database (code: `val1` and `val2`) are those that pertain to "centered forecasts" (code: `fdesc=1,2`) in millions or billions of USD. We mainly study forecasts of future revenue (code: `measure=SAL`), although we also consider forecasts of future profits (code: `measure=NET`) and earnings per share (code: `measure=`cpx).

We define a firm's forecast error of a variable as the difference between the realized value of the variable from Compustat and the one-year-ahead forecast of the variable from I/B/E/S.

Descriptive Statistics: We report descriptive statistics for our data set in Table A.1.

[38] For an individual firm, we study the first forecast made in the year (Jan-April) that pertains to the firm's end-of-year financial results. Firms mainly report previous year's financial results in Q1 of the following year.

Table A.1: Descriptive Statistics: I/B/E/S-Compustat

Variable Name	Obs.	Mean	Std.	Median
Revenue	12,917	3,762	11,518	769.49
Profits	12,917	279.30	1,403	28.98
Capital	12,825	1,052	4,692	122.79
Investment	12,910	184.13	857.47	46.70
Wages	845	1,841	3,974	353.89
Debt	12,870	1,259	8,858	46.70
Assets	12,917	5,720	22,152	1012.85
Employment	12,835	12.90	32.42	2.90
Revenue/capital	12,821	13.23	32.16	6.97
Forecast/capital	12,821	14.71	51.24	7.00
Forecast Log	12,821	1.94	1.13	1.95
Forecast Error	12,567	-0.14	1.91	0.01
Forecast Error Log	12,563	-0.01	0.13	0.00

Notes: The table reports descriptive statistics for the sample of 2,570 firms from 2002-2022 in the combined Compustat-I/B/E/S database. The units of the first seven rows are USD millions. The employment row is in '000-employees. The first eight rows capture, respectively, firm revenue, GAAP net-profits, book value of the capital stock, total value of capital expenditures, end-of-period total liabilities and assets, overall expenditures to labor and related expenses, and the total number of employees. The next three rows measure revenue scaled by a firm's tangible capital and the (log) of the year-ahead forecast. The final two rows are for the year-ahead forecast error defined as realized future (log)-revenue minus (log of) the forecast. In the final two rows, observations have been removed that are in top and bottom one percent of the error distribution.

A.2 Data Construction: Duke-Richmond Fed CFO Survey

The CFO Survey is a quarterly survey of U.S. business leaders designed to elicit the financial outlook for their firms, the challenges they face, and their expectations about the U.S. economy. We exploit a combination of survey answers from The CFO Survey and data on economy-wide outcomes from FRED. The sample covers the period 2020-2022, the period for which data is available, for 3,470 firm-years spanning 826 US firms. We remove forecasts that are not one-year-ahead forecasts, as well as any firm-years that have non-existing profits. We throughout focus on annualized real GDP growth forecasts (code: `GDPC1`). The treatment of the I/B/E/S-Compustat sample is described above. Firm size is measured by the number of domestic full-time employees. The size buckets used below correspond to quintiles of the 2020 size distribution: `size=1` (fewer than 6 employees); `size=2` (6-40 employees); `size=3` (40-130 employees); `size=4` (130-500 employees); and `size=5` ($>$ 500 employees). The familiarity with the concept of GDP is measured numerically with a scale from 1-3.

A.3 Additional Data Comments

In this appendix, we provide a brief overview of the relationship between firms' revenue expectations and their input choices in the I/B/E/S-Compustat data set. First, notice that firms' revenue errors are close to unbiased: Table A.1 shows that the mean error of firms' log revenue errors is, for example, -0.01 compared to an average value of log revenue of 1.94. This result is consistent with the evidence in, e.g., Chen *et al.* (2023) , who show that Japanese firms' expectations about their own sales, in addition to their expectations about macroeconomic and sector-specific inflation rates, are close to unbiased. All else equal, firms in our sample do not appear to systematically skew their revenue expectations one way or another. Relatedly, Chen *et al.* (2024) explore how positive and negative E/P/S forecast revisions respond to new information in the I/B/E/S-Compustat data set, finding also a consistent pattern.

Second, Table A.2 conducts an exercise akin to that in Tanaka *et al.* (2020). Panel a documents the relationship between the realized growth in inputs and the current-period (firm-specific) expectation of *future revenue*. We find that, all else equal, more optimistic firms employ and investment more, consistent with these firms being more viewed as more optimistic. The estimated effect sizes are, furthermore, substantial: a 1 percent increase in expected revenue is associated with 0.14 percent increase in investment, for example. In Section 6.1 in the main text, we discuss how the *accuracy* of firms' expectations, in addition to their level, systematically affect firms' input choices, consistent with our model framework. Panel b in Table A.2 instead explores the relationship between the realized growth in various inputs and the *previous period's revenue error*. We find that firms that have been positively surprised—i.e., have higher revenue than previously expected, and hence a positive revenue error—subsequently employ and invest more, in line with these firms being genuinely surprised about the revenue realization. We conclude that the results in Table A.2 are consistent with the those in Tanaka *et al.* (2020), among others, who show that firms who are more optimistic about the future invest and employ more, and that positive profit (or revenue) surprises result in more inputs being employed subsequently.

Finally, we note that the arguments we provide in the main text do not require that firms' reported expectations to strictly equal their (correct) mathematical expectation of future revenue. We do not require the complete absence of strategic or behavioral drivers of expectations. We only require that changes in reported expectations (and in their accuracy) in part reflect changes in information.The results in Table A.1 and A.2 are consistent with this role of information. The results in Table A.5, which show that larger firms in the Duke-Richmond CFO survey report more accurate expectations of a variable (real GDP growth) over which they have no control, further bolsters this case.

Table A.2: Expectations and Input Choices

	Panel a: outcomes and expectations		
	Employment (%)	Capital (%)	Investment (%)
Revenue expectation (%)	0.069***	0.222***	0.139*
	(0.026)	(0.085)	(0.078)
Firm age (quintile)	-2.072	-5.794	-0.014
	(1.627)	(4.198)	(1.725)
Observations	10,260	10,277	10,255
Firm FE	✓	✓	✓
Time FE	✓	✓	✓
F statistic	52.856***	137.772***	26.116***
	Panel b: outcomes and errors		
	Employment (%)	Capital (%)	Investment (%)
Revenue error lagged (%)	0.188***	0.195	0.661**
	(0.053)	(0.266)	(0.312)
Firm age (quintile)	-2.492	-7.159	-0.888
	(1.772)	(4.733)	(2.079)
Observations	10,020	10,096	10,069
Firm FE	✓	✓	✓
Time FE	✓	✓	✓
F statistic	4.210**	3.228**	5.3786***

Notes: Panel least-squares estimates from the merged I/B/E/S-Compustat sample. Panel a: estimate of the relationship between realized growth in employment (capital and investment) and the current-period firm-specific forecasts of revenue growth. Panel b: estimate of the relationship between realized growth in employment (capital and investment) and the one-period lagged revenue error. The table also controls for a firm's age, measured in quintiles of the overall age distribution. Forecasts (errors) related to the top and bottom 1 percent of forecast errors have been removed. All estimates controls for time and firm fixed effects. Robust (clustered) standard errors in parentheses. Sample: 2002–2022.

A.4 Additional Estimates

Table A.3: Time evolution of accuracy and size

	Panel (a): revenue errors and time			
	Absolute error		Squared error	
	(1)	(2)	(3)	(4)
Time	-0.024^{***}	-0.015^{***}	-0.028^{***}	-0.024^{***}
	(0.003)	(0.002)	(0.007)	(0.005)
Constant	1.251^{***}	1.135^{***}	1.303^{***}	1.219^{***}
	(0.037)	(0.026)	(0.085)	(0.065)
Observations	12,567	12,563	12,567	12,563
Covid dummy	×	✓	×	✓
Residual std. error	1.835	1.278	4.302	3.148
F statistic	67.11^{***}	57.23^{***}	17.70^{***}	22.59^{***}
	Panel (b): size and time			
	50th perc.	70th perc.	80th perc.	90th perc.
	(1)	(2)	(3)	(4)
Time	0.011^{***}	0.012^{***}	0.009^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.567^{***}	0.374^{***}	0.215^{***}	0.111^{***}
	(0.015)	(0.016)	(0.007)	(0.005)
Observations	21	21	21	21
Residual std. error	0.029	0.032	0.021	0.014
F statistic	119.85^{***}	115.36^{***}	153.64^{***}	98.96^{***}

Notes: Panel least-squares estimates from the merged I/B/E/S-Compustat sample. Panel (a): estimate of the coefficient of the absolute value (squared value) of individual one-year ahead revenue errors on time. Revenue errors are scaled by a firm's tangible capital stock and normalized by the overall average absolute (squared) error in the sample. The top and bottom 1 percent of errors have been removed. Panel (b): estimate of the coefficient of the share of firms with employment greater than the xth percentile of firms in 2002 on time. Columns (1) and (3) are in levels, whereas Columns (2) and (4) pertain to the logs of variables. Robust standard errors in parentheses. Sample: 2002–2022.

Table A.4: Time evolution of accuracy: sector fixed effects

	Panel (a): sector fixed effects			
	Absolute error		Squared error	
	(1)	(2)	(3)	(4)
Time	-0.024^{***}	-0.016^{***}	-0.027^{***}	-0.026^{***}
	(0.003)	(0.002)	(0.007)	(0.005)
Constant	0.586^{***}	1.818^{**}	0.405^{***}	3.472
	(0.117)	(0.860)	(0.106)	(2.738)
Observations	12,567	12,563	12,567	12,563
Covid dummy	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Residual std. error	1.814	1.269	4.282	3.141
F statistic	17.32^{***}	13.71^{***}	7.15^{***}	5.66^{***}

	Panel (b): sector×time fixed effects			
	Absolute error		Squared error	
	(1)	(2)	(3)	(4)
Time	-0.023^{***}	-0.011^{***}	-0.028^{***}	-0.020^{***}
	(0.003)	(0.002)	(0.007)	(0.005)
Constant	1.246^{***}	1.114^{***}	1.301^{***}	1.209^{***}
	(0.033)	(0.026)	(0.082)	(0.067)
Observations	12,567	12,563	12,567	12,563
Sector×time FE	✓	✓	✓	✓
Residual std. error	1.652	1.257	4.184	3.176
F statistic	79.09^{***}	29.37^{***}	18.52^{***}	15.54^{***}

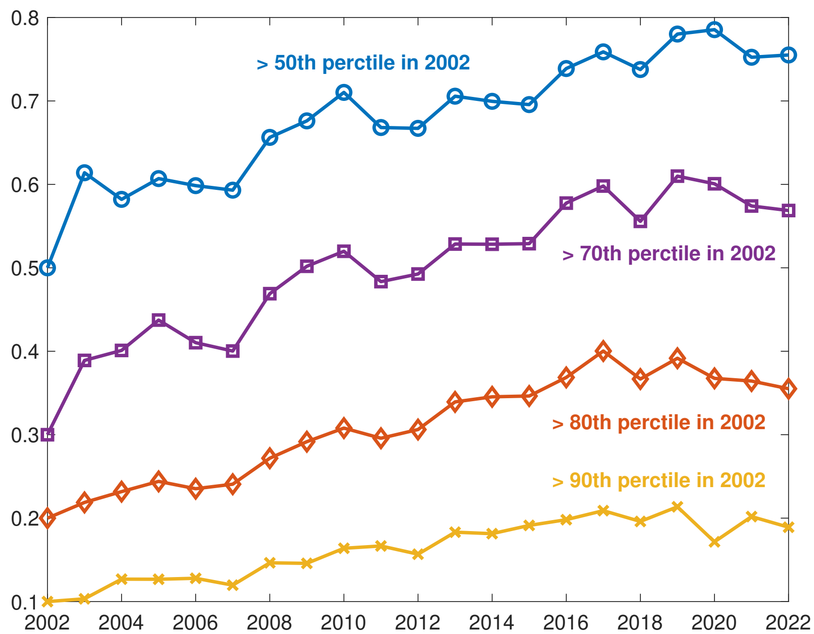
Notes: Panel least-squares estimates from the merged I/B/E/S-Compustat sample. Panel (a): estimate of the coefficient of the absolute value (squared value) of individual one-year ahead revenue errors on time, after having partialled out for sector (NAICS-2) fixed effects and a COVID dummy. Revenue errors are scaled by a firm's tangible capital stock and normalized by the overall average absolute (squared) error in the sample. The top and bottom 1 percent of errors have been removed. Panel (b) instead partials out for sector×time fixed effects beforehand. Columns (1) and (3) are in levels, whereas Columns (2) and (4) pertain to the logs of variables. Robust standard errors in parentheses. Sample: 2002–2022.

Table A.5: Output expectations from the Duke CFO Survey

	Squared error		Absolute error	
	(1)	(2)	(3)	(4)
Firm size	-0.077^{**}	-0.060^{*}	-0.050^{***}	-0.045^{***}
	(0.028)	(0.024)	(0.012)	(0.010)
GDP familiarity		0.033		0.018
		(0.043)		(0.025)
Constant	1.639^{***}	1.676^{***}	1.648^{***}	1.681^{***}
	(0.115)	(0.090)	(0.051)	(0.042)
Observations	1,584	1,464	1,584	1,464
Sector FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Residual std. error	1.578	1.544	0.812	0.793
F Statistic	19.774^{***}	20.165^{***}	29.175^{***}	29.814^{***}

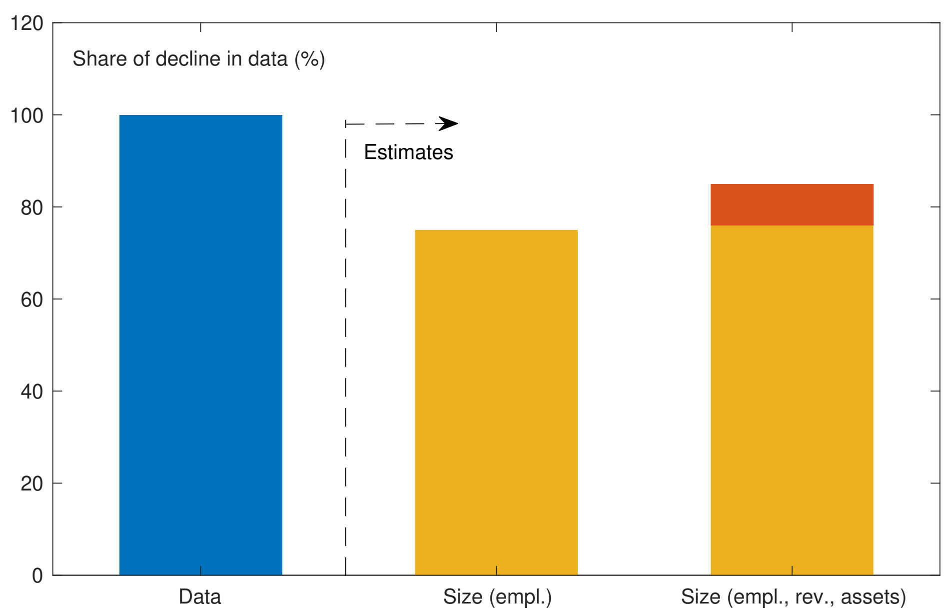
Notes: Estimates from the Duke CFO Survey. Column (1) shows estimates from a regression of the square of individual one-year-ahead real GDP growth errors on firm size (employment) and sector and time fixed effects. Firm size is measured discretely (values 1-5), depending on which quintile firm employment is in relative to the 2020-employment distribution. Column (2) controls for the familiarity of the respondent to the concept of GDP. Columns (3) and (4) consider the absolute value of individual errors. GDP errors are normalized by the overall average squared (absolute) error in the sample. The top and bottom 1 percent of errors have been removed. Robust clustered standard errors in parentheses. Sample: 2020-2022.

Figure A.1: Time evolution of firm size



Note: Data from the I/B/E/S-Compustat sample. The figure shows the share of firms in a given year with employment exceeding the xth percentile of the 2002-employment distribution. The 50th, 80th, 90th percentile of the 2002-employment distribution correspond to around 1,000, 7,000, and 18,000 employees, respectively. Table A.3 in the Appendix shows the associated regression results pertaining to the percentage increase.

Figure A.2: Size and uncertainty simulation



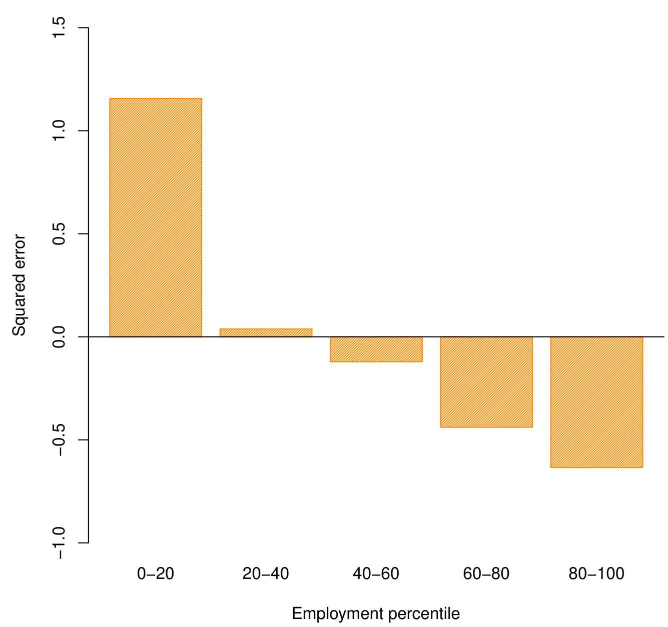
Note: The figure shows the overall decline in revenue uncertainty in the I/B/E/S-Compustat sample (Figure 1) from its average value in 2002-2005 to 2022. The figure compares the decline to that implied from the change in the firm-size distribution, using the estimates in Table I Column 4 (with/without the inclusion of real firm assets and real firm revenue as further control variables). Firm real revenue (assets) are measured by the quintile the firm's revenue (assets) are in at time t relative to the 2002-revenue (asset) distribution. Firms revenue and assets are deflated by CPI-U from FRED.

Table A.6: Time evolution of asset size

	Panel (b): asset size and time*			
	50th perc.	70th perc.	80th perc.	90th perc.
	(1)	(2)	(3)	(4)
Time	0.013***	0.011***	0.007***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.408***	0.282***	0.164***	0.102***
	(0.016)	(0.011)	(0.005)	(0.005)
Observations	21	21	21	21
Residual std. error	0.031	0.026	0.016	0.016
F Statistic	126.291***	150.569***	145.456***	62.575***

Notes: Panel estimates from the merged I/B/E/S-Compustat sample. The table estimates the coefficients of the share of firms with assets greater than the xth percentile of firms in 2002 on time. Assets are deflated by CPI-U from FRED. Robust standard errors in parentheses. The 50th, 70th, 80th, and 90th percentile of the 2002-asset distribution correspond to c. 288, 512, 992, and 3,728 million USD. Sample: 2002–2022.

Figure A.3: Revenue expectations across the asset distribution



Note: The figure plots the difference between the average squared error of one-year-ahead log-revenue forecasts from the I/B/E/S-Compustat merger within size (asset) quintiles and the overall average taken across all size levels. Revenue errors are scaled by a firm's tangible capital stock and normalized by their mean value in the sample. Table A.7 reports the coefficient estimates, controlling for firm characteristics. Sample: 2002-2022.

Table A.7: Robustness of revenue expectations, firm size, and time relationship

	Absolute error		*Squared error*		*Squared error log*
	(1)	(2)	(3)	(4)	(5)
Firm size	-0.353^{***}	-0.293^{***}	-0.560^{***}	-0.450^{***}	
	(0.034)	(0.040)	(0.072)	(0.084)	
Firm assets					-0.243^{***}
					(0.056)
Time	-0.006		-0.003		
	(0.006)		(0.012)		
Firm age	0.004	0.023	0.046	0.058	0.022
	(0.016)	(0.024)	(0.035)	(0.052)	(0.031)
Rev. volatility		0.010^{***}		0.010^{**}	0.004
		(0.002		(0.002)	(0.011)
Observations	12,489	6,819	12,489	6,819	6,834
Time FE	×	✓	×	✓	✓
Sector FE	✓	✓	✓	✓	✓
F Statistic	10.460^{***}	7.704^{***}	5.494^{***}	5.043^{***}	2.083^{***}

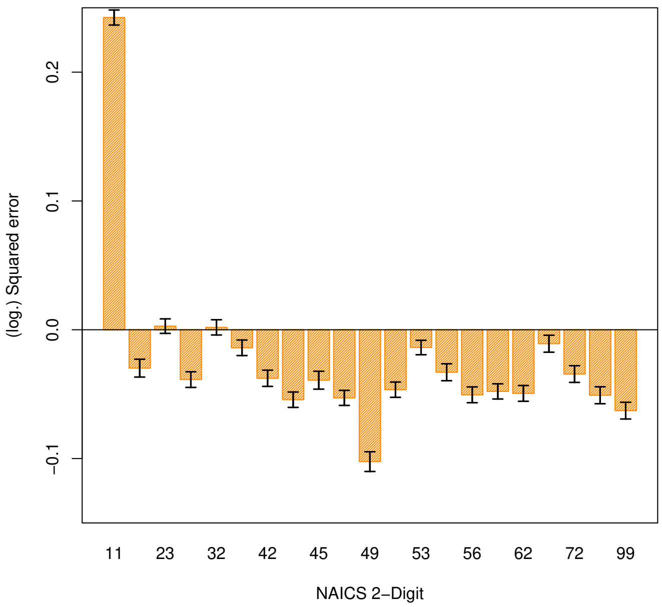
Notes: Panel estimates from the merged I/B/E/S-Compustat sample. Column (1) shows estimates from a regression of the absolute value of individual one-year-ahead revenue errors on firm size (employment), controlling for time and firm age and sector fixed effects (NAICS-4). Firm size is measured based on which quintile the firm's employment level is at time t relative to the 2002-employment distribution. Column (2) considers the same regression specification but includes time fixed effects, as well as the rolling four-year volatility of revenue. Columns (3) and (4) consider the same specifications studied in Columns (1) and (2), but instead use the squared value of individual errors as the dependent variable. Finally, Column (5) uses the squared value of individual one-year-ahead revenue errors, and measures firm size based on which quintile the firm's asset level is at time t relative to the asset distribution. Revenue errors are scaled by a firm's tangible capital stock and normalized by the overall average absolute (squared) error. The top and bottom 1 percent of forecast errors have been removed. Robust (clustered) standard errors in parentheses. Sample: 2002-2022.

Table A.8: Revenue expectations, firm size, and fixed effects

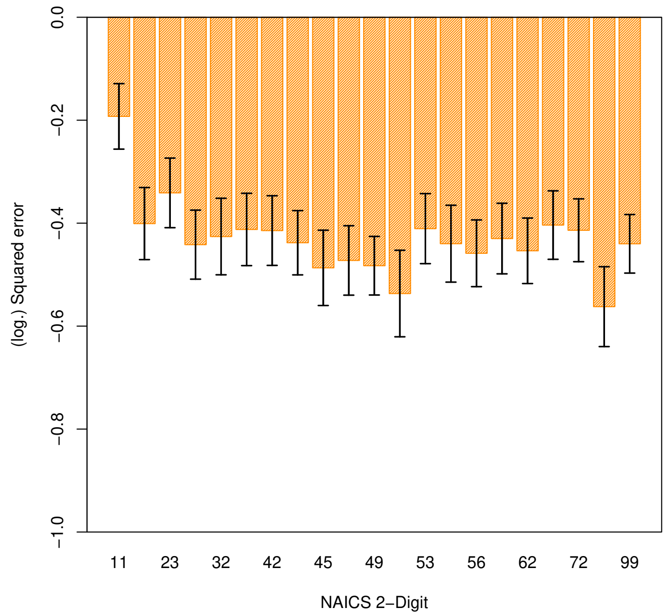
	Squared log-revenue error		
	(1)	(2)	(3)
Firm size	-0.343^{***}	-0.438^{***}	-0.316^{***}
	(0.068)	(0.054)	(0.064)
Firm age	0.054^{*}		0.023
	(0.030)		(0.029)
Log. revenue volatility	-0.006		-0.006
	(0.011)		(0.011)
Observations	6,809	12,488	6,809
Sector FE	✓	×	×
Time FE	✓	×	×
Time×Sector FE	×	✓	✓
F statistic	2.441^{***}	2.401^{***}	1.438^{***}

Notes: Panel estimates from the merged I/B/E/S-Compustat sample. Column (1) shows estimates of the squared value of one-year-ahead log-revenue errors on firm size (employment) and sector (NAICS-4) and time fixed effects. We also control for firm age and the individual four-year-rolling average of the volatility of revenue. Firm size is measured by the quintile the firm's employment is at time t relative to the 2002-employment distribution. Columns (2) and (3) adds time×sector (NAICS-2) fixed effects. Revenue errors are scaled by firm capital and normalized by the overall average absolute error. The top and bottom 1 percent of errors have been removed. Robust (clustered) standard errors in parentheses. Sample: 2002-2022.

Figure A.4: Sectoral heterogeneity and the time and size relationship



Panel (a): Time relationship



Panel b: Size relationship

Note: Panel least-squares estimates from the merged I/B/E/S-Compustat sample. Panel (a): estimate of the coefficient of the squared value of individual one-year-ahead (log-) revenue errors on time for different NAICS 2-digit sectors. Panel (b): estimate of the coefficient of the squared value of individual one-year-ahead (log-) revenue errors on firm size for different NAICS 2-digit sectors. Firm size is measured measured by the quintile the firm's employment is at time t relative to the 2002-employment distribution. Robust (clustered) standard errors in parentheses. Sample: 2002–2022.

Table A.9: Other variables (profits and capex)

	Panel (a): errors and time			
	Profits		Capex	
	Abs. error	Sqr. error	Abs. error	Sqr. error
Time	-0.039^{***}	-0.068^{***}	-0.012^{***}	0.001
	(0.010)	(0.024)	(0.003)	(0.011)
Constant	1.398^{***}	1.691^{***}	1.126^{***}	0.986^{***}
	(0.126)	(0.303)	(0.035)	(0.120)
Observations	2,487	2,487	1,839	1,839
Residual std. error	2.482	6.187	1.871	6.982
F statistic	15.27^{***}	7.385^{***}	12.91^{***}	0.011
	Panel (b): errors and size			
	Profits		Capex	
	Abs. error	Sqr. error	Abs. error	Sqr. error
Firm size	-0.361^{***}	-0.578^{***}	-0.074^{***}	-0.130^{***}
	(0.082)	(0.195)	(0.018)	(0.047)
Firm age	-0.029	0.047	-0.070^{***}	-0.117^{*}
	(0.080)	(0.147)	(0.016)	(0.061)
Constant	0.456	0.680	-0.113^{***}	-0.144
	(0.314)	(0.486)	(0.042)	(0.165)
Observations	2,487	2,487	1,839	1,839
Sector FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Residual std. error	2.347	6.209	1.740	6.744
F statistic	2.694^{***}	1.056	7.906^{***}	2.849^{***}

Notes: Panel estimates from the merged I/B/E/S-Compustat sample. Panel (a): estimate of the coefficient of the absolute value (squared value) of individual one-year ahead profit (capex) errors on time. Forecast errors are scaled by a firm's tangible capital stock and normalized by the overall average absolute (squared) error in the sample. The top and bottom 1 percent of errors have been removed. Panel (b): estimate of the coefficient of the absolute value (squared value) of individual one-year ahead errors on firm size, controlling for firm age, and time and sector (NAICS level 4) fixed effects. Firm size is measured as in Table I. Robust (clustered) standard errors in parentheses. Sample: 2004–2022 (profits) and 2002–2022 (capex).

Table A.10: Percentage increase in revenue

	Absolute error		*Squared error*		
	(1)	(2)	(3)	(4)	(5)
Firm size	-0.210^{***}	-0.177^{***}	-0.372^{***}	-0.308^{***}	
	(0.025)	(0.031)	(0.056)	(0.064)	
Time	0.0005		0.005		-0.014^{**}
	(0.004)		(0.008)		(0.007)
Firm age	-0.050^{***}	0.009	-0.095^{**}	0.026	
	(0.016)	(0.025)	(0.039)	(0.051)	
Rev. volatility (pct.)		0.004^{***}		0.005^{***}	
		(0.001)		(0.002)	
Observations	10,083	5,700	10,083	5,700	10,138
Time FE	×	✓	×	✓	×
Sector FE	✓	✓	✓	✓	×
F Statistic	5.589^{***}	4.648^{***}	3.491^{***}	3.163^{***}	6.747^{***}

Notes: Panel estimates from the merged I/B/E/S-Compustat sample. Column (1) shows estimates from a regression of the absolute value of individual one-year-ahead revenue growth errors (in pct.) on firm size (employment), controlling for time and firm age and sector fixed effects (NAICS-4). Firm size is measured based on which quintile the firm's employment level is at time t relative to the 2002-employment distribution. Column (2) considers the same specification but includes time fixed effects, as well as the rolling four-year volatility of revenue. Columns (3) and (4) consider the same specifications studied in Columns (1) and (2), but instead use the squared value of individual errors as the dependent variable. Finally, Column (5) considers the raw correlation with time. Revenue errors are scaled by a firm's tangible capital stock and normalized by the overall average absolute (squared) error. The top and bottom 1 percent of forecast errors have been removed. Robust (clustered) standard errors in parentheses. Sample: 2002-2022.

Table A.11: Large acquisitions and forecast accuracy

	Squared error	Absolute error
	(1)	(2)
Large acquisitions	-0.140^{*}	-0.061^{*}
	(0.007)	(0.033)
Large acquisitions(-1)	-0.119^{*}	-0.082^{***}
	(0.066)	(0.031)
Large acquisitions(-2)	-0.106^{*}	-0.079^{***}
	(0.062)	(0.031)
Large acquisitions(-3)	0.040	-0.040
	(0.068)	(0.031)
Firm age	0.038	0.005
	(0.034)	(0.017)
Log revenue volatility	0.027^{**}	0.017^{***}
	(0.013)	(0.005)
Observations	5,108	5,108
Sector FE	✓	✓
Time FE	✓	✓
Residual std. error	2.324	1.048
F statistic	1.569^{***}	2.954^{***}

Notes: Panel least-squares estimates from the merged I/B/E/S-Compustat sample. The table estimates the coefficient of the squared value (absolute value) of individual one-year-ahead log-revenue errors on firm acquisitions, controlling for firm age, revenue volatility (rolling 4-year average), and time and sector (NAICS level 4) fixed effects. Errors are scaled by a firm's tangible capital stock and normalized by the overall average squared (absolute) error in the sample. The top and bottom 1 percent of errors have been removed. A large acquisitions is defined as one above 5 percent of a firm's assets, consistent with the definition in Ottonello and Winberry (2020). Robust (clustered) standard errors in parentheses. Sample: 2002–2022.

Table A.12: Accuracy and intangible capital

	Accuracy of expectations	
	Sqr. error	Abs. error
Firm acq. stock of intangibles	-0.070*	-0.038***
	(0.040)	(0.015)
Firm size	-0.405***	-0.211***
	(0.041)	(0.019)
Firm age	-0.051	-0.034***
	(0.034)	(0.013)
Observations	11,371	11,371
Sector FE	✓	✓
Time FE	✓	✓
F statistic	3.721***	6.499***

Notes: Panel least-squares estimates from the I/B/E/S-Compustat sample. The table estimates the relationship between of the stock of acquired intangibles and the uncertainty surrounding firms' log-revenue forecasts. The stock of acquired intangibles accounts adjusts amortization and take-outs financial goodwill (Compustat: `INTAN+AM-GDWL`), and the nominal stock is deflated. This is in accordance with Chiavari and Goraya (2023). Column (1) considers the squared value of individual errors, while Column (2) considers the absolute value. Errors are normalized by the overall average squared (absolute) error in the sample. The top and bottom 1 percent of errors have been removed. All estimates controls for time and sector (NAICS-4) fixed effects. Robust (clustered) standard errors in parentheses. Sample: 2002–2022.

B Proofs and Derivations for Sections 3 and 4

Consumer Tastes. Here, we provide a simple microfoundation for the formulation of household preferences in (1). Suppose that instead the utility of household i is given by:

$$\mathcal{U}^i = C^i = \left[\int_0^1 \left(\delta^{\mathrm{r}}_{ij} \cdot c^{\mathrm{r}}_{ij} + \delta^{\mathrm{b}}_{ij} \cdot c^{\mathrm{b}}_{ij}\right)^{\frac{\theta-1}{\theta}} \cdot dj\right]^{\frac{\theta}{\theta-1}}, \tag{A1}$$

where c^{r}_{ij} and c^{b}_{ij} are the consumptions of the red- and blue-type variety j respectively, and where δ^{r}_{ij} and δ^{b}_{ij} are taste shocks. These taste shocks have a noisy mapping to the demand state ω_j. In particular:

$$\delta^{\mathrm{r}}_{ij} = \begin{cases} \delta_H & \text{if } \widetilde{\omega}^{\mathrm{r}}_{ij} = 1 \\ \delta_L & \text{otherwise} \end{cases} \text{ and } \delta^{\mathrm{b}}_{ij} = \begin{cases} \delta_H & \text{if } \widetilde{\omega}^{\mathrm{b}}_{ij} = 1 \\ \delta_L & \text{otherwise} \end{cases}, \tag{A2}$$

where $\widetilde{\omega}^{\mathrm{r}}_{ij}$ and $\widetilde{\omega}^{\mathrm{b}}_{ij}$ are random variables that take values in $\{0, 1\}$ and, conditional on the demand state $\omega_j \in \{\text{red}, \text{blue}\}$, they are distributed independently across households and varieties as follows:

$$\mathbb{P}\left(\widetilde{\omega}^{\mathrm{r}}_{ij} = 1 | \omega_j = \text{red}\right) = \bar{\gamma} > \underline{\gamma} = \mathbb{P}\left(\widetilde{\omega}^{\mathrm{r}}_{ij} = 1 | \omega_j = \text{blue}\right), \tag{A3}$$

and

$$\mathbb{P}\left(\widetilde{\omega}^{\mathrm{b}}_{ij} = 1 | \omega_j = \text{blue}\right) = \bar{\gamma} > \underline{\gamma} = \mathbb{P}\left(\widetilde{\omega}^{\mathrm{b}}_{ij} = 1 | \omega_j = \text{red}\right). \tag{A4}$$

Given this formulation, if the demand state is ω_j and if the variety j supplied in the market in equilibrium is of type $x_j = \omega_j$, then for a share $\bar{\gamma}$ of households:

$$\delta^{\mathrm{r}}_{ij} \cdot c^{\mathrm{r}}_{ij} + \delta^{\mathrm{b}}_{ij} \cdot c^{\mathrm{b}}_{ij} = \delta_H \cdot c_{ij}, \tag{A5}$$

and for the remaining share:

$$\delta^{\mathrm{r}}_{ij} \cdot c^{\mathrm{r}}_{ij} + \delta^{\mathrm{b}}_{ij} \cdot c^{\mathrm{b}}_{ij} = \delta_L \cdot \cdot c_{ij}, \tag{A6}$$

where c_{ij} are the units of the variety consumed by household i. If instead the variety j available in the market is of type $x_j \neq \omega_j$, then for a share $\underline{\gamma}$ of households:

$$\delta^{\mathrm{r}}_{ij} \cdot c^{\mathrm{r}}_{ij} + \delta^{\mathrm{b}}_{ij} \cdot c^{\mathrm{b}}_{ij} = \delta_H \cdot c_{ij}, \tag{A7}$$

and for the remaining share:

$$\delta^{\mathrm{r}}_{ij} \cdot c^{\mathrm{r}}_{ij} + \delta^{\mathrm{b}}_{ij} \cdot c^{\mathrm{b}}_{ij} = \delta_L \cdot c_{ij}, \tag{A8}$$

where c_{ij} are the units of the variety consumed by household i.

Therefore, given the types of their varieties chosen by firms in equilibrium, this formulation of household preferences coincides with that in Equation (1) in the main text. $\square$

Proof of Proposition 1. Using the household demand in (9) and market clearing for variety j, for a given choices of inputs and information, (x_j, n_j, ι_j), firm j's expected profits are:

$$\mathbb{E}\left[\pi_j|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]=\mathbb{E}\left[\left(\delta_j\cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]\cdot n_j^{\frac{\theta-1}{\theta}}\cdot C^{\frac{1}{\theta}}-w\cdot\left(n_j+\chi\cdot\iota_j\right),\tag{A9}$$

where δ_j is given by Equation (9), and where due to independence of the shocks υ_j and ω_j:

$$\mathbb{E}\left[\left(\delta_j\cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]=\mathbb{E}\left[\delta_j^{\frac{\theta-1}{\theta}}|s_j^{\omega},\tau_j^{\omega}\right]\cdot\mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}}|\mu_j,s_j^{\upsilon},\tau_j^{\upsilon}\right].\tag{A10}$$

Using the properties of γ_j in Equation (2), we have that:

$$\mathbb{E}\left[\delta_j^{\frac{\theta-1}{\theta}}|s_j^{\omega},\tau_j^{\omega}\right]=\mathbb{P}\left(\omega_j=x_j|s_j^{\omega},\tau_j^{\omega}\right)\cdot\delta\left(\bar{\gamma}\right)^{\frac{\theta-1}{\theta}}+\left(1-\mathbb{P}\left(\omega_j=x_j|s_j^{\omega},\tau_j^{\omega}\right)\right)\cdot\delta\left(\underline{\gamma}\right)^{\frac{\theta-1}{\theta}}.\tag{A11}$$

Now, because the demand shifter of the "representative consumer" is strictly higher when the firm customizes the variety to its tastes, i.e., $\delta\left(\bar{\gamma}\right)>\delta\left(\underline{\gamma}\right)$, and because signals are weakly informative, firm j optimally chooses:

$$x_j=s_j^{\omega}\in\{\text{red},\text{blue}\}\quad\Longrightarrow\quad\mathbb{P}\left(\omega_j=x_j|s_j^{\omega},\tau_j^{\omega}\right)=\tau_j^{\omega}.\tag{A12}$$

As a result, maximizing expected profits in Equation (A9) with respect to n_j yields:

$$n_j=\mathbb{E}\left[\left(\delta_j\cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]^{\theta}\cdot\Omega,\tag{A13}$$

as stated in the proposition. Lastly, plugging back the optimal choices of x_j and n_j into the expression for expected profits in Equation (A9), we get:

$$\mathbb{E}\left[\pi_j|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]=\frac{1}{\theta-1}\cdot\mathbb{E}\left[n_j|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]-\chi\cdot\iota_j.\tag{A14}$$

Thus, at *Stage 1*, the firm produces information if and only if:

$$\frac{1}{\theta-1}\cdot\left(\mathbb{E}\left[n_j|\mu_j,\bar{\boldsymbol{\tau}}_j\right]-\mathbb{E}\left[n_j|\mu_j,\underline{\boldsymbol{\tau}}_j\right]\right)\geq\chi.\tag{A15}$$

Finally, to arrive at the expression for the expected employment in the text, observe that:

$$\mathbb{E}\left[\delta_j^{\frac{\theta-1}{\theta}}|s_j^\omega, \tau_j^\omega\right] = \tau_j^\omega \cdot \delta\left(\bar{\gamma}\right)^{\frac{\theta-1}{\theta}} + \left(1-\tau_j^\omega\right) \cdot \delta\left(\underline{\gamma}\right)^{\frac{\theta-1}{\theta}}, \tag{A16}$$

which is independent of the realization of s_j^ω, and:

$$\mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}}|\mu_j, s_j^\upsilon, \tau_j^\upsilon\right] = \exp^{\frac{\theta-1}{\theta}\cdot\mu_j} \cdot \exp^{\frac{\theta-1}{\theta}\cdot\frac{\tau_j^\upsilon}{\tau_j^\upsilon+\tau_a}\cdot s_j^\upsilon + \frac{1}{2}\cdot\left(\frac{\theta-1}{\theta}\right)^2\cdot\frac{1}{\tau_j^\upsilon+\tau_a}}, \tag{A17}$$

which implies that:

$$\mathbb{E}\left[\mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}}|\mu_j, s_j^\upsilon, \tau_j^\upsilon\right]^\theta |\mu_j, \tau_j^\upsilon\right] = \exp^{(\theta-1)\cdot\mu_j} \cdot \exp^{\frac{1}{2}\cdot\frac{(\theta-1)^2}{\theta}\cdot\frac{\tau_a+\theta\cdot\tau_j^\upsilon}{\tau_a+\tau_j^\upsilon}\cdot\frac{1}{\tau_a}}. \tag{A18}$$

Therefore, the expected employment of firm j, conditional on its information choice is:

$$\begin{aligned}\mathbb{E}\left[n_j|\mu_j, \boldsymbol{\tau}_j\right] &= \left[\tau_j^\omega \cdot \delta\left(\bar{\gamma}\right)^{\frac{\theta-1}{\theta}} + \left(1-\tau_j^\omega\right) \cdot \delta\left(\underline{\gamma}\right)^{\frac{\theta-1}{\theta}}\right]^\theta \cdot \exp^{(\theta-1)\cdot\mu_j} \cdot \exp^{\frac{1}{2}\cdot\frac{(\theta-1)^2}{\theta}\cdot\frac{\tau_a+\theta\cdot\tau_j^\upsilon}{\tau_a+\tau_j^\upsilon}\cdot\frac{1}{\tau_a}} \cdot \Omega \\ &= \exp^{(\theta-1)\cdot\mu_j} \cdot g\left(\boldsymbol{\tau}_j\right)^{\theta-1} \cdot \Omega, \end{aligned} \tag{A19}$$

where $g(\cdot)$ is as defined in Equation (15). □

Proof of Corollary 1. The proof follows from the definition of tfp_j in Equation (19), the fact that firm optimality implies that, conditional on $(\mu_j, \boldsymbol{\tau}_j)$, the demand shifter δ_j (as defined by Equation (9)) equals $\delta(\bar{\gamma})$ with probability τ_j^ω and $\delta(\underline{\gamma})$ with probability $1-\tau_j^\omega$, combined with the fact that $\log(A_j)|\mu_j \sim \mathcal{N}(\mu_j, \tau_a^{-1})$. □

Proof of Corollary 2. From the optimality condition for n_j in Equation (12), we have:

$$\text{mrp}_j = \log\left(p_j \cdot y_j\right) - \log\left(\mathbb{E}\left[p_j \cdot y_j|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]\right) - \log\left(\frac{\theta}{\theta-1}\cdot w\right). \tag{A20}$$

It therefore follows immediately that:

$$\mathbb{VAR}\left[\text{mrp}_j|\mu_j, \boldsymbol{\tau}_j\right] = \mathbb{VAR}\left[\text{error}_j|\mu_j, \boldsymbol{\tau}_j\right]. \tag{A21}$$

Next, using household demand and market clearing for variety j, we have that firm j's revenues are given by the expression:

$$p_j \cdot y_j = \left(\delta_j \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}}. \tag{A22}$$

Thus, we have that:

$$\begin{aligned}
\text{error}_j &= \frac{\theta-1}{\theta}\cdot\left(\log\left(\delta_j\cdot A_j\right)-\mathbb{E}\left[\log\left(\delta_j\cdot A_j\right)|\mu_j,\boldsymbol{s}_j,\boldsymbol{\tau}_j\right]\right)\\
&= \frac{\theta-1}{\theta}\cdot\left(\log\left(\delta_j\right)-\mathbb{E}\left[\log\left(\delta_j\right)|\tau_j^{\omega}\right]\right)+\frac{\theta-1}{\theta}\cdot\left(\log\left(A_j\right)-\mathbb{E}\left[\log\left(A_j\right)|\mu_j,s_j^{\upsilon},\tau_j^{\upsilon}\right]\right)\\
&= \frac{\theta-1}{\theta}\cdot\left(\log\left(\delta_j\right)-\mathbb{E}\left[\log\left(\delta_j\right)|\tau_j^{\omega}\right]\right)+\frac{\theta-1}{\theta}\cdot\left(\frac{\tau_j^{a}}{\tau_j^{\upsilon}+\tau_a}\cdot\upsilon_j-\frac{\tau_j^{\upsilon}}{\tau_j^{\upsilon}+\tau_a}\cdot\varepsilon_j\right). \qquad \text{(A23)}
\end{aligned}$$

Therefore:

$$\begin{aligned}
\mathbb{VAR}\left[\text{mrp}_j|\mu_j,\boldsymbol{\tau}_j\right] &= \left(\frac{\theta-1}{\theta}\right)^2\cdot\mathbb{VAR}\left[\log\left(\delta_j\right)|\tau_j^{\upsilon}\right]+\left(\frac{\theta-1}{\theta}\right)^2\cdot\frac{1}{\tau_j^{\upsilon}+\tau_a} \qquad \text{(A24)}\\
&= \mathbb{VAR}\left[\text{tfp}_j|\mu_j,\tau_j^{\upsilon}\right]+\left(\frac{\theta-1}{\theta}\right)^2\cdot\left(\frac{1}{\tau_j^{\upsilon}+\tau_a}-\frac{1}{\tau_a}\right). \qquad \text{(A25)}
\end{aligned}$$

□

Proof of Corollary 3. The expression for the marginal-type $\bar{\mu}$ that is just indifferent to producing information follows from the optimality condition for information production in Equation (17) and the expression for a firm's expected employment in Equation (18). Next, consider two firms, j and j', with mean productivities $\mu_j < \bar{\mu} < \mu_{j'}$, so that firm j' produces information while firm j does not.

First, the statement that firm j' on average has a higher and less dispersed tfp_j follows from Corollary 1 and the fact that $\mu_{j'} > \mu_j$ and $\tau_{j'}^{\omega} > \tau_j^{\omega}$.

Second, the statement that firm j' has less dispersed mrp_j follows from Corollary 2 and the fact that $\mu_{j'} > \mu_j$ and $\tau_{j'}^{\upsilon} > \tau_j^{\upsilon}$, combined with the fact that it has less dispersed tfp_j.

Finally, that $\mathbb{E}[n_{j'}|\mu_{j'},\boldsymbol{\tau}_{j'}] > \mathbb{E}[n_j|\mu_j,\boldsymbol{\tau}_j]$ follows from the expression for a firm's expected size in Equation (18), the definition of the information shifter in Equation (15), combined with the fact that $\mu_{j'} > \mu_j$ and $\boldsymbol{\tau}_{j'} > \boldsymbol{\tau}_j$. Clearly, it then also follows that (i) $\mathbb{E}[n_{j'}|\mu_{j'},\boldsymbol{\tau}_{j'}]+\chi\cdot\iota_{j'} > \mathbb{E}[n_j|\mu_j,\boldsymbol{\tau}_j]+\chi\cdot\iota_j$, since $\iota_{j'} = 1 > 0 = \iota_j$; and (ii) $\mathbb{E}[p_{j'}\cdot y_{j'}|\mu_{j'},\boldsymbol{\tau}_{j'}] > \mathbb{E}[p_j\cdot y_j|\mu_j,\boldsymbol{\tau}_j]$ and $\mathbb{E}[p_{j'}\cdot y_{j'}-w\cdot n_{j'}|\mu_{j'},\boldsymbol{\tau}_{j'}] > \mathbb{E}[p_j\cdot y_j-w\cdot n_j|\mu_j,\boldsymbol{\tau}_j]$, since both are proportional to a firm's expected employment (Equation 18). Lastly, it follows that expected profits are higher for j', since firm j' has chosen to produce information. □

Proof of Lemma 1. Equation (28) in the text follows by using the definition of aggregate TFP, $\mathcal{A}$, and the definition of aggregate employment in goods production, $\mathcal{N}$, combined with the optimality conditions in Proposition 1. Moreover:

$$\int_0^1 \mathbb{E}\left[\left(\delta_j \cdot A_j\right)^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj = \int_0^1 \exp^{(\theta-1)\cdot\mu_j} \cdot g\left(\boldsymbol{\tau}_j\right)^{\theta-1} \cdot dj$$
$$= g\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \int_{-\infty}^{\bar{\mu}} \exp^{(\theta-1)\cdot\mu} \cdot d\Phi\left(-\mu \cdot \sqrt{\tau_\mu}\right) + g\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \int_{\bar{\mu}}^{\infty} \exp^{(\theta-1)\cdot\mu} \cdot d\Phi\left(-\mu \cdot \sqrt{\tau_\mu}\right), \quad \text{(A26)}$$

where, using the definition $\xi\left(\bar{\mu}\right) \equiv \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_\mu} + \frac{\theta-1}{\sqrt{\tau_\mu}}\right)$, we have:

$$\int_{\bar{\mu}}^{\infty} \exp^{(\theta-1)\cdot\mu} \cdot d\Phi\left(-\mu \cdot \sqrt{\tau_\mu}\right) = \int_{\bar{\mu}}^{\infty} \frac{1}{\sqrt{2 \cdot \pi \cdot \tau_\mu}} \cdot \exp^{-\mu^2 \cdot \frac{1}{2} \cdot \tau_\mu + (\theta-1)\cdot\mu} \cdot d\mu \quad = \exp^{\frac{1}{2} \cdot \frac{(\theta-1)^2}{\tau_\mu}} \cdot \xi\left(\bar{\mu}\right),$$

and, similarly:

$$\int_{\bar{\mu}}^{\infty} \exp^{(\theta-1)\cdot\mu} \cdot d\Phi\left(-\mu \cdot \sqrt{\tau_\mu}\right) = \exp^{\frac{1}{2} \cdot \frac{(\theta-1)^2}{\tau_\mu}} \cdot \left(1 - \xi\left(\bar{\mu}\right)\right). \quad \text{(A27)}$$

The result then follows by replacing these expressions into Equation (28). □

Proof of Proposition 3. Combining Equations (26) and (31), together with the expression for aggregate TFP in Lemma 1, we have that the equilibrium $\mu^\star$ satisfies:

$$\exp^{(\theta-1)\cdot\mu^\star} = \exp^{\frac{1}{2} \cdot \frac{(\theta-1)^2}{\tau_\mu}} \cdot (\theta - 1) \cdot \chi \cdot \frac{\frac{g(\underline{\boldsymbol{\tau}})^{\theta-1}}{g(\bar{\boldsymbol{\tau}})^{\theta-1} - g(\underline{\boldsymbol{\tau}})^{\theta-1}} + \xi\left(\mu^\star\right)}{N - \chi \cdot \Phi\left(-\mu^\star \cdot \sqrt{\tau_\mu}\right)}. \quad \text{(A28)}$$

The left-hand side of Equation (A28) is monotonically increasing in $\mu^\star$, whereas the right-hand side is monotonically decreasing in $\mu^\star$. As a result, either a decline in χ or a rise in $\bar{\boldsymbol{\tau}}$, both of which imply a decline in the right-hand side, lead to a decline in $\mu^\star$ and thus a rise in the share of firms that produce information. From Lemma 1, it then follows that aggregate TFP rises as well; in the case of a rise in $\bar{\boldsymbol{\tau}}$ it rises both directly as $g\left(\bar{\boldsymbol{\tau}}\right)$ and indirectly through the fall in $\mu^\star$. As for aggregate consumption and welfare, it is straightforward to show that Equation (A28) implies that:

$$\frac{d}{d\bar{\mu}} \cdot \left(\mathcal{A}\left(\bar{\mu}, g\right) \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_\mu}\right)\right]\right) |_{\bar{\mu}=\mu^\star} = 0. \quad \text{(A29)}$$

Hence, by an envelope argument, we need only consider the direct effect of changes in χ or $\bar{\boldsymbol{\tau}}$ on $C^\star$. But, these are clearly positive, since, for a given $\mu^\star$, a lower χ reduces costs of information production, whereas a higher $\bar{\boldsymbol{\tau}}$ raises aggregate TFP. □

C Proofs and Derivations for Section 5

Optimal Trading Mechanism. We now provide detailed derivations for the optimal trading mechanism of Section 5.1. Since at *Stage* 3, the firm's supply of variety j is inelastic and given by $Q_j = A_j \cdot n_j$, the firm's objective is to maximize the revenues collected from the consumers (Equation 34) subject to incentive compatibility (Equation 35), individual rationality (Equation 36), and feasibility (Equation 37) constraints.

We conjecture (and then verify) that the individual rationality (IR) constraint of the H-type and the incentive compatibility (IC) constraint of the L-type are slack. Given this, the firm's problem becomes:

$$\max_{\left(t_j^H, q_j^H\right), \left(t_j^L, q_j^L\right) \text{ with } q_j^L, q_j^H \geq 0} \quad \gamma_j \cdot t_j^H + (1-\gamma_j) \cdot t_j^L \tag{A30}$$

s.t.

$$\left(\delta_H \cdot q_j^H\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j^H \geq \left(\delta_H \cdot q_j^L\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j^L, \tag{A31}$$

$$\left(\delta_L \cdot q_j^L\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j^L \geq 0, \tag{A32}$$

$$\gamma_j \cdot q_j^H + (1-\gamma_j) \cdot q_j^L \leq Q_j. \tag{A33}$$

By inspection, it is optimal for the firm to set t_j^L and t_j^H so that both the IC-constraint of the H-type and the IR-constraint of the L-type bind. Moreover, it is clear that the firm will allocate all of its goods to the consumers, so that the feasibility constraint binds. As a result, the problem reduces to:

$$\max_{q_j^L, q_j^H \geq 0} \ \gamma_j \cdot \delta_H^{\frac{\theta-1}{\theta}} \cdot q_j^{H\frac{\theta-1}{\theta}} + \left(\delta_L^{\frac{\theta-1}{\theta}} - \gamma_j \cdot \delta_H^{\frac{\theta-1}{\theta}}\right) \cdot q_j^{L\frac{\theta-1}{\theta}} \tag{A34}$$

s.t.

$$\gamma_j \cdot q_j^H + (1-\gamma_j) \cdot q_j^L = Q_j. \tag{A35}$$

Clearly, if $\gamma_j = 0$, then the firm only faces L-type consumers and, thus, it is optimal to set $q_j^L = Q_j$. In this case, the firm is indifferent to any q_j^H and for convenience we suppose that $q_j^H \geq q_j^L$. If $\gamma_j \geq (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$, it is optimal for the firm to exclude the L-type consumer and set $q_j^H = \gamma_j^{-1} \cdot Q_j \geq 0 = q_j^L$. Finally, for $\gamma_j \in (0, (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}})$, the allocation of goods is interior and given by:

$$q_j^L = \frac{(\psi_j \cdot \delta_L)^{\theta-1}}{\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot (\psi_j \cdot \delta_L)^{\theta-1}} \cdot Q_j \text{ and } q_j^H = \frac{\delta_H^{\theta-1}}{\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot (\psi_j \cdot \delta_L)^{\theta-1}} \cdot Q_j, \tag{A36}$$

where ψ_j is given in Equation (40) in the main text. The expressions for the shares α_j^L and α_j^H in Equations (39) and (38) then follow immediately.

Denote the optimal allocation of the type-l consumer by $\left(t_j^{l\star}, q_j^{l\star}\right)$, and let us verify the conjecture that the IC-constraint of the L-type and the IR-constraint of the H-type are satisfied at the optimum. The latter follows by combining the binding IC-constraint of the H-type and the binding IR-constraint of the L-type:

$$t_j^{H\star} = \left(\delta_H \cdot q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - \left(\delta_H^{\frac{\theta-1}{\theta}} - \delta_L^{\frac{\theta-1}{\theta}}\right) \cdot \left(q_j^{L\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} \leq \left(\delta_H \cdot q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}}. \tag{A37}$$

The former follows from the fact that $q_j^{L\star} \leq q_j^{H\star}$ and, again, by combining the binding IC-constraint of the H-type and the binding IR-constraint of the L-type:

$$\begin{aligned}\left(\delta_L \cdot q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - t_j^{H\star} &= \left(\delta_L \cdot q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - \left[\left(\delta_H \cdot q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - \left(\delta_H^{\frac{\theta-1}{\theta}} - \delta_L^{\frac{\theta-1}{\theta}}\right) \cdot q_j^{L\star\frac{\theta-1}{\theta}}\right] \\ &= \left(\delta_L^{\frac{\theta-1}{\theta}} - \delta_H^{\frac{\theta-1}{\theta}}\right) \cdot \left[\left(q_j^{H\star}\right)^{\frac{\theta-1}{\theta}} - \left(q_j^{L\star}\right)^{\frac{\theta-1}{\theta}}\right] \cdot C^{\frac{1}{\theta}} \leq 0, \end{aligned} \tag{A38}$$

and the L-type earns zero surplus at the optimal allocation.

We now derive the expression for the L-type consumer's surplus earned from a given allocation $\left(t_j^l, q_j^l\right)$ offered by the mechanism, which we had assumed in the above derivations. To this end, note that the utility that consumer i gains from consuming q_{ij} units of variety j, when her overall consumption is C_i, is given by:

$$\widetilde{u}_{ij}\left(q_{ij}\right) = \frac{\theta}{\theta-1} \cdot \left(\delta_{ij} \cdot q_{ij}\right)^{\frac{\theta-1}{\theta}} \cdot C_i^{\frac{1}{\theta}}. \tag{A39}$$

Suppose that λ_i is the marginal value of income to the consumer, expressed in units of the aggregate consumption bundle, which we assume is the numeraire. Then, the surplus of the consumer in units of the numeraire is $\frac{\widetilde{u}_{ij}(q_{ij})}{\lambda_i}$. Since households are ex-ante identical, in any symmetric equilibrium it must be that $\lambda_i = \lambda$ and $C_i = C$ for all i. In equilibrium, therefore, aggregation implies that $\lambda = \frac{\theta}{\theta-1}$. Because in equilibrium all agents have correct expectations about λ and C, they understand that consumer i's willingness to pay for q_{ij} units of its variety is $\left(\delta_{ij} \cdot q_{ij}\right)^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}}$, as assumed in the main text.

Now, in the above, we assumed that the representative household's marginal value of income, λ, is well defined. For this to be the case, we need to be able to assign a utility value to an additional unit of income in the hands of the household. However, if firms were only offering the bundles $\left\{\left(t_j^{l\star}, q_j^{l\star}\right)\right\}$, which are all accepted in equilibrium, the household would have no opportunities to spend this additional income. To address this issue, we follow an approach similar to Bornstein and Peter (2024), and suppose that firms post additional latent allocations in their menus, which are not accepted in equilibrium but ensure that the consumer faces linear prices off-equilibrium. Thus, suppose that, in addition to the bundles $\left\{\left(t_j^{l\star}, q_j^{l\star}\right)\right\}$, each firm j offers to sell to the consumer any quantity $q > q_j^H$ for a total payment of:

$$t_j\left(q\right) = t_j^{H\star} + \kappa_j^\star \cdot \left(q - q_j^{H\star}\right) \text{ with } \kappa_j^\star = \delta_H^{\frac{\theta-1}{\theta}} \cdot \left(q_j^{H\star}\right)^{-\frac{1}{\theta}} \cdot C^{\frac{1}{\theta}}. \tag{A40}$$

By construction, no bundle with $q > q_j^{H\star}$ is picked up in equilibrium by the household with a marginal value of income $\lambda = \frac{\theta}{\theta-1} = (\kappa_j^\star)^{-1} \cdot \tilde{u}_{Hj}(q_j^{H\star})$, where the right-hand side is the marginal gain in utility to the H-type household per unit of the numeraire that is spent on obtaining an additional unit above $q_j^{H\star}$. Moreover, the marginal value of income to the household is now well defined, since she can now spend the additional income (if she had any) to obtain units above $q_j^{H\star}$ for the varieties for which she is an H-type. $\square$

Alternative Trading Environments. The trading mechanism that we considered in Section 5 resembles that of a centralized market for each variety j, in which price discrimination occurs through quantity bundles. Here, we provide two alternative specifications, which generalize our results to markets where goods trade in a decentralized fashion, or where goods are indivisible and discrimination occurs through quality differentiation.

Bargaining in Decentralized Markets. Consider now a decentralized marketplace, in which each firm j meets each consumer on an "island" and engages in bargaining. In particular, as in Section 5.1, the firm proposes menus to the consumer; however, due to a "search friction" the firm is unable to ship the goods across islands.[39] This implies that the feasibility constraint in (37) must now replaced by $q_j^l \leq Q_j$.

Following in the same footsteps of the derivation of the optimal mechanism of Section 5.1 (see above), we can show that the solution to this mechanism design problem is as follows:

- If $\gamma_j \geq (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$, then $\alpha_j^H = \gamma_j^{-1} \cdot Q_j > 0 = \alpha_j^L$;
- If $\gamma_j < (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$, then $\alpha_j^H = \alpha_j^L = 1$;

where α_j^l denotes the share of its goods that firm j allocates to type-l consumer. Thus, we see that firm j either excludes the L-type completely or trades with both consumer types the

[39]If the firm could ship goods freely across islands, then the allocations of the optimal mechanism would coincide with those of the mechanism in Section 5.1.

entire quantity on equal terms. Analogously to Section 5.2, we can derive the revenue- and surplus-based demand shifters also in this setting:

$$\delta_j^R = \begin{cases} \delta_L \\ \gamma_j^{\frac{\theta}{\theta-1}} \cdot \delta_H \end{cases} \qquad \delta_j^S = \begin{cases} (\gamma_j \cdot \delta_H^{\frac{\theta-1}{\theta}} + (1-\gamma_j) \cdot \delta_L^{\frac{\theta-1}{\theta}})^{\frac{\theta}{\theta-1}} & \text{if } \gamma_j < (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}} \\ \gamma_j^{\frac{\theta}{\theta-1}} \cdot \delta_H & \text{otherwise} \end{cases}. \tag{A41}$$

The properties of these two demand shifters, which are central to all of the positive and normative results in Section 5, are just as stated in Lemma 2. Namely, (i) the revenue-based demand shifter, δ_j^R, is increasing in γ_j (strictly so for $\gamma_j \geq (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$); (ii) the surplus-based demand shifter, δ_j^R is non-monotonic in γ_j (in this setting, this feature always arises); and (iii) the ratio δ_j^S/δ_j^R increases at first (i.e., in the region $\gamma_j < (\delta_L/\delta_H)^{\frac{\theta-1}{\theta}}$) and then decreases in γ_j.

Quality Differentiation. Consider a simple reformulation of our setting that captures trade in indivisible goods. More concretely, let us suppose that each consumer demands a single unit of each variety j, but where c_{ij} in the consumer's preferences in (1) captures the quality of the good instead. In turn, suppose that at *Stage 3*, each firm j can use its units of effective labor, $A_j \cdot n_j$, to create goods of high quality, q_j^H, and low quality, q_j^L, and sell them to consumers at prices t_j^H and t_j^L, respectively. It is then straightforward to show that the allocations of this economy are identical to that of our rent-extracting economy studied in Section 5. □

Proof of Lemma 2. See text. □

Proof of Proposition 4. The result follows immediately from the observation that the ex-post profits of firm j in the rent-extracting economy are given by Equation (41). □

Proof of Proposition 5. Given the equilibrium $\mu^\star$, the aggregate TFP of the rent-extracting economy is given by:

$$\begin{aligned}
\mathcal{A} = C \cdot \mathcal{N}^{-1} &= \frac{\left(\int_0^1 \left[\gamma_j \cdot \delta_H^{\frac{\theta-1}{\theta}} \cdot \alpha_j^{H\frac{\theta-1}{\theta}} + (1-\gamma_j) \cdot \delta_L^{\frac{\theta-1}{\theta}} \cdot \alpha_j^{L\frac{\theta-1}{\theta}}\right] \cdot (A_j \cdot n_j)^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj} \\
&= \frac{\left(\int_0^1 \left(\delta_j^S \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj} \\
&= \frac{\left(\int_0^1 \mathbb{E}\left[\delta_j^{S\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot \mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot n_j^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj} \\
&= \frac{\left(\int_0^1 \mathbb{E}\left[\delta_j^{S\frac{\theta-1}{\theta}} | \tau_j^\omega\right] \cdot \mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot n_j^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj},
\end{aligned} \tag{A42}$$

where the second equality follows from the definition of δ_j^S in Equation (44); the third equality follows from the observation that δ_j^S is independent of A_j, conditional on firm j's information set $(\mu_j, \boldsymbol{\tau}_j, \boldsymbol{s}_j)$; and the last equality follows from the fact that optimal product choice $x_j = s_j^\omega$ implies $\mathbb{E}\left[\delta_j^{S\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] = \mathbb{E}\left[\delta_j^{S\frac{\theta-1}{\theta}}|\tau_j^\omega\right]$. Using the definition of the gap, $\Delta(\boldsymbol{\tau})$, between profit and social surplus maximization in Equation (46), we thus get that:

$$
\begin{aligned}
\mathcal{A} &= \frac{\left(\int_0^1 \frac{\mathbb{E}\left[\delta_j^{S\frac{\theta-1}{\theta}}|\tau_j^\omega\right]}{\mathbb{E}\left[\delta_j^{R\frac{\theta-1}{\theta}}|\tau_j^\omega\right]} \cdot \mathbb{E}\left[\delta_j^{R\frac{\theta-1}{\theta}}|\tau_j^\omega\right] \cdot \mathbb{E}\left[A_j^{\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot n_j^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj} \\
&= \frac{\left(\int_0^1 \Delta\left(\boldsymbol{\tau}_j\right)^{\frac{\theta-1}{\theta}} \cdot \mathbb{E}\left[\left(\delta_j^R \cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot n_j^{\frac{\theta-1}{\theta}} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 n_j \cdot dj} \\
&= \frac{\left(\int_0^1 \Delta\left(\boldsymbol{\tau}_j\right)^{\frac{\theta-1}{\theta}} \cdot \mathbb{E}\left[\left(\delta_j^R \cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj\right)^{\frac{\theta}{\theta-1}}}{\int_0^1 \mathbb{E}\left[\left(\delta_j^R \cdot A_j\right)^{\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right]^{\theta} \cdot dj} \\
&= \exp^{\frac{\theta-1}{2}\cdot\frac{1}{\tau_\mu}} \cdot \frac{\left[\Delta\left(\underline{\boldsymbol{\tau}}\right)^{\frac{\theta-1}{\theta}} \cdot g^R\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \left(1-\xi\left(\mu^\star\right)\right) + \Delta\left(\bar{\boldsymbol{\tau}}\right)^{\frac{\theta-1}{\theta}} \cdot g^R\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \xi\left(\mu^\star\right)\right]^{\frac{\theta}{\theta-1}}}{g^R\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \left(1-\xi\left(\mu^\star\right)\right) + g^R\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} \cdot \xi\left(\mu^\star\right)} \\
&= \mathcal{E}\left(\mu^\star\right) \cdot \mathcal{A}(\mu^\star, g^R),
\end{aligned} \tag{A43}
$$

where the second equality follows from the fact that $x_j = s_j^\omega$ implies that $\mathbb{E}\left[\delta_j^{R\frac{\theta-1}{\theta}}|\mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] = \mathbb{E}\left[\delta_j^{R\frac{\theta-1}{\theta}}|\tau_j^\omega\right]$; the third equality follows from the optimal labor choice in Proposition 4; and the last two equalities follow from the definition of the information shifter $g^R(\cdot)$ in Equation (45), the expressions for $\xi(\mu^\star)$ and $\mathcal{A}(\mu^\star, g)$ in Lemma 1, as well as the definition of the macro-wedge, $\mathcal{E}$, in Equation (49). Given the expression for aggregate TFP, the expression for aggregate consumption then follows immediately. □

Proof of Corollary 4. See text. □

Proof of Proposition 6. Consider the problem of the social planner as described in Section 5.5. To solve this problem, we will begin with the conjecture that, given a quantity $Q_j = A_j \cdot n_j$ produced by firm j, the planner can allocate consumption across the two types of consumers freely, subject to the feasibility constraint:

$$
\gamma_j \cdot c_{Hj} + (1-\gamma_j) \cdot c_{Lj} \leq Q_j, \tag{A44}
$$

i.e., for now we ignore the fact that the planner also faces incentive compatibility and participation constraints. We will later show that the resulting allocations can be implemented as an outcome of a mechanism that satisfies these constraints, just as the privately described trading mechanisms in Section 5.1.

Given this conjecture, the planner will equalize marginal utilities across types:

$$\delta_H^{\frac{\theta-1}{\theta}} \cdot c_{Hj}^{-\frac{1}{\theta}} = \delta_L^{\frac{\theta-1}{\theta}} \cdot c_{Lj}^{-\frac{1}{\theta}} \implies c_{lj} = \widetilde{\alpha}_j^l\left(\gamma_j\right) \cdot Q_j, \tag{A45}$$

where $\widetilde{\alpha}_j^l\left(\gamma_j\right)$ is the share of the good allocated to type-l consumer, and it is the same as the share $\alpha_j^l\left(\gamma_j\right)$ given in Equations (38) and (39), except that the micro-wedge, ψ_j, equals one.

Let λ denote the marginal value of a unit of labor to the social planner, i.e., the multiplier on the aggregate resource constraint $\int_0^1 \left(n_j + \chi \cdot \iota_j\right) \cdot dj \leq N$. Given the above consumption allocation, it follows that the ex-post surplus (in terms of utils) produced by firm j that chooses (x_j, n_j, ι_j) can be expressed as:

$$u_j\left(x_j, n_j, \iota_j, \upsilon_j, \omega_j\right) = \frac{\theta}{\theta-1} \cdot \left(\delta_j \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - \lambda \cdot \left(n_j + \chi \cdot \iota_j\right) \tag{A46}$$

where $\delta_j = \left(\gamma_j \cdot \delta_H^{\theta-1} + (1-\gamma_j) \cdot \delta_L^{\theta-1}\right)^{\frac{1}{\theta-1}}$ is the demand shifter defined in Equation (9). Thus, at *Stage 2*, the social planner's choices (x_j, n_j, ι_j) are similar to those in Proposition 1:

$$x_j = s_j^{\omega} \text{ and } n_j = \mathbb{E}\left[\left(\delta_j \cdot A_j\right)^{\frac{\theta-1}{\theta}} | \mu_j, \boldsymbol{s}_j, \boldsymbol{\tau}_j\right] \cdot \widetilde{\Omega}, \tag{A47}$$

where the effective "market size" faced by the planner is now $\widetilde{\Omega} \equiv \frac{C}{\lambda^{-\theta}}$, and:

$$\iota_j = \begin{cases} 1 & \text{if } \frac{1}{\theta-1} \cdot \left(\mathbb{E}\left[n_j | \mu_j, \bar{\boldsymbol{\tau}}\right] - \mathbb{E}\left[n_j | \mu_j, \underline{\boldsymbol{\tau}}\right]\right) \geq \chi \\ 0 & \text{otherwise} \end{cases}, \tag{A48}$$

with expected employment of firm j given by:

$$\mathbb{E}\left[n_j | \mu_j, \boldsymbol{\tau}_j\right] = \exp^{(\theta-1)\cdot\mu_j} \cdot g\left(\boldsymbol{\tau}_j\right)^{\theta-1} \cdot \widetilde{\Omega}. \tag{A49}$$

Thus, at the planner's allocation, firm j produces information if and only if

$$\mu_j \geq \bar{\mu}\left(\widetilde{\Omega}\right) = \frac{1}{\theta-1} \cdot \log\left[\frac{(\theta-1)\cdot\chi}{\left(g\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} - g\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1}\right) \cdot \widetilde{\Omega}}\right], \tag{A50}$$

which note is the same schedule as that given in Equation (26). Since the planner does not leave any labor unused, if we take as given the marginal type $\bar{\mu}$ that produces information, the aggregate resource constraint yields the expression for the "market size" faced by the planner:

$$\widetilde{\Omega} = \widetilde{\Omega}\left(\bar{\mu}\right) = \frac{\mathcal{A}\left(\bar{\mu}, g\right) \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)\right]}{\mathcal{A}\left(\bar{\mu}, g\right)^{\theta}}, \tag{A51}$$

where $\mathcal{A}\left(\cdot\right)$ is as given by Lemma 1. This schedule is also the same as the one in Equation (31). As a result, the allocations of the social planner coincide with those of our baseline economy: the marginal type that produces information is given by the intersection of the above two schedules:

$$\mu^{\star} = \bar{\mu}\left(\widetilde{\Omega}\left(\mu^{\star}\right)\right), \tag{A52}$$

and the aggregate TFP and welfare are in turn given by:

$$\mathcal{A}^{\star} = \mathcal{A}\left(\mu^{\star}, g\right) \text{ and } C^{\star} = \mathcal{A}^{\star} \cdot \left[N - \chi \cdot \Phi\left(-\mu^{\star} \cdot \sqrt{\tau_{\mu}}\right)\right]. \tag{A53}$$

As there are increasing returns to information production, we must nevertheless still verify that $\mu^{\star} = \arg\max_{\bar{\mu}} \mathcal{A}\left(\mu^{\star}, g\right) \cdot \left[N - \chi \cdot \Phi\left(-\mu^{\star}\right)\right]$, i.e., that the amount of information production chosen above actually maximizes welfare. But, this follows from the observation that:

$$\begin{aligned} &\frac{d}{d\bar{\mu}}\left(\mathcal{A}\left(\bar{\mu}, g\right) \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)\right]\right) \propto \\ &\propto \left(\theta - 1\right) \cdot \chi \cdot \frac{1}{g\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} - g\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1}} \cdot \frac{\mathcal{A}\left(\bar{\mu}, g\right)^{\theta-1}}{N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_{\mu}}\right)} - \exp^{(\theta-1)\cdot\bar{\mu}}, \end{aligned} \tag{A54}$$

where the right-hand side is positive (negative) whenever $\bar{\mu} < \mu^{\star}$ ($\bar{\mu} > \mu^{\star}$).

Lastly, we verify the conjecture that the allocations of the planner are incentive compatible and individually rational. To this end, consider the following menu provided to consumers of each variety j by the social planner: $\mathcal{M} = \left\{\left(t_j, q_j\right)\right\}_{q_j \geq 0}$ where q_j is the quantity of the good transferred to the consumer and t_j is the transfer of the numeraire good C from the consumer to the planner—which is then rebated lump sum to the consumer. The transfer schedule in turn satisfies:

$$t_j = t\left(q_j\right) = \left[\delta_H^{\frac{\theta-1}{\theta}} \cdot q_j^{H\star - \frac{1}{\theta}} \cdot C^{\star\frac{1}{\theta}}\right] \cdot q_j, \tag{A55}$$

where the superscript $\star$ indicates the allocations of the social planner that we obtained above (e.g., $q_j^{H\star} = \widetilde{\alpha}_j^H\left(\gamma_j\right) \cdot A_j \cdot n_j^{\star}$). Note that, since the marginal utilities across consumer types are equalized, it must also be that $t_j = \left[\delta_L^{\frac{\theta-1}{\theta}} \cdot q_j^{L\star - \frac{1}{\theta}} \cdot C^{\star\frac{1}{\theta}}\right] \cdot q_j$. Given this menu, and the conjectured equilibrium allocations, a consumer of type-l indeed optimally chooses $q_j = q_j^{l\star}$ since it equalizes her marginal utility to her marginal cost. Therefore, by revealed preference, the planner's allocations are incentive compatible and individually rational.

We have thus shown that the social planner's allocations coincide with those of our baseline economy. Since the equilibrium of the rent-extracting economy generically differs from the equilibrium of our baseline economy (except in the case where $0 = \underline{\gamma} < \bar{\gamma} = 1$), we conclude that it must generically be inefficient. $\square$

Proof of Proposition 7. Following in the steps of Proposition 6, we know that the marginal type $\mu^\star$ that is just indifferent to producing information in the laissez-faire equilibrium of the rent-extracting economy is the unique maximizer of:

$$\mathcal{A}(\bar{\mu}, g^R) \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_\mu}\right)\right]. \tag{A56}$$

It therefore follows that the optimal information tax, which selects $\bar{\mu}$ to maximize:

$$\mathcal{E}\left(\bar{\mu}\right) \cdot \mathcal{A}\left(\bar{\mu}, g^R\right) \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_\mu}\right)\right] \tag{A57}$$

is positive (negative) if $\mathcal{E}'\left(\cdot\right) > 0$ (< 0), since $\mathcal{E}'\left(\cdot\right) \gtreqless 0$ iff $\delta^S\left(\bar{\gamma}\right)/\delta^R\left(\bar{\gamma}\right) \lesseqgtr \delta^S\left(\underline{\gamma}\right)/\delta^R\left(\underline{\gamma}\right)$. $\square$

Proof of Proposition 8. From Proposition 2, the aggregate TFP and consumption in the rent extracting economy are:

$$\mathcal{A}^\star = \mathcal{E}\left(\mu^\star\right) \cdot \mathcal{A}\left(\mu^\star, g^R\right) \text{ and } C^\star = \mathcal{A}^\star \cdot \left[N - \chi \cdot \Phi\left(-\mu^\star \cdot \sqrt{\tau_\mu}\right)\right],$$

where $\mu^\star$ is the equilibrium marginal type as characterized by Proposition 1.

Let us first suppose that we are in the parametric case where rent extraction is socially destructive. Given any $\bar{\mu}$ and any garbling policy about productivity information, z^υ, both $\mathcal{E}\left(\bar{\mu}\right)$ and $\mathcal{A}\left(\bar{\mu}, g^R\right)$ are increasing in z^ω. At the maximum when $z^\omega = 1$, $\mathcal{E}\left(\bar{\mu}\right)$ becomes independent of $\bar{\mu}$ and recall $\mathcal{E}\left(\cdot\right)$ also does not depend on z^υ. Thus, $z^\omega = 1$ is optimal for the planner and, given $z^\omega = 1$, an optimal garbling policy also sets $z^\upsilon = 0$, since $\mathcal{A}\left(\bar{\mu}, g^R\right)|_{z^\upsilon, z^\omega = 1}$ is decreasing in z^υ for a given $\bar{\mu}$.[40] Lastly, given the optimal garbling policy, $z^\omega = 1$ and $z^\upsilon = 0$, by the same arguments as in the proof of Proposition 7, the optimal information tax T must be zero, since the equilibrium selects the marginal type that is the maximizer of $\mathcal{A}\left(\bar{\mu}, g^R\right)|_{z^\omega = 1, z^\upsilon = 0} \cdot \left[N - \chi \cdot \Phi\left(-\bar{\mu} \cdot \sqrt{\tau_\mu}\right)\right]$, which maximizes social welfare, since under the optimal garbling policy, $\mathcal{E}\left(\cdot\right)$ is independent of $\bar{\mu}$.

Next, suppose that we are in the parametric case where rent extraction is not socially destructive. Arguments analogous to those above imply that, for any given $\bar{\mu}$ and z^ω, $\mathcal{E}\left(\bar{\mu}\right) \cdot$

[40] The conditioning on (z^υ, z^ω) in $\mathcal{A}\left(\bar{\mu}, g^R\right)|_{z^\omega, z^\upsilon}$ simply indicates that we are evaluating TFP with the information shifter, in which the precision of produced information is $(\underline{\tau}^\upsilon + z^\upsilon \cdot (\bar{\tau}^\upsilon - \underline{\tau}^\upsilon), \underline{\tau}^\omega + z^\omega \cdot (\bar{\tau}^\omega - \underline{\tau}^\omega))$.

$\mathcal{A}\left(\bar{\mu}, g^R\right)$ is decreasing z^v. Therefore, the social planner again sets $z^v = 0$. $\square$

Second-Best Policies. In Section 5.5, we focused on interventions that solely target the economy's information structure. In this section, we consider a broader set of interventions, which are still constrained to take the firms' pricing strategies as given.

As we have already shown, conditional on the allocations induced by privately optimal mechanisms—i.e., the shares α_j^l in Equations (38) and (39)—the only deviation from social surplus maximization occurs because firms make their information and input choices based on the revenue-based demand shifter, δ_j^R, rather than the social-surplus based shifter, δ_j^S. A policy correcting this misalignment is therefore sufficient to achieve "second-best efficiency."

To this end, consider firm j's ex-post profits, augmented by a revenue subsidy S_j:

$$\pi_j = (1 + S_j) \cdot \left(\delta_j^R \cdot A_j\right)^{\frac{\theta-1}{\theta}} \cdot n_j^{\frac{\theta-1}{\theta}} \cdot C^{\frac{1}{\theta}} - w \cdot n_j - w \cdot \chi \cdot \iota_j. \tag{A58}$$

By setting the subsidy to:

$$S_j = S(\gamma_j) = \left[\frac{\delta^S(\gamma_j)}{\delta^R(\gamma_j)}\right]^{\frac{\theta-1}{\theta}} - 1, \tag{A59}$$

the social planner ensures that firm j maximizes social surplus when making its information and input choices, (x_j, n_j, ι_j) (Equation (43)). Among interventions that maintain the privately optimal trading mechanisms, the subsidy scheme $\{S_j\}_j$, financed through lump-sum taxes on households achieves the highest social welfare. Although this "second-best" policy is more complex and requires policymakers to understand the composition of consumers faced by each firm, it exhibits parallels with the optimal data regulation discussed in Section 5.5.

First, consider the case where rent extraction is severe but not socially destructive, i.e., $\delta^S(\bar{\gamma})/\delta^R(\bar{\gamma}) < \delta^S(\underline{\gamma})/\delta^R(\underline{\gamma})$ but $\delta^S(\bar{\gamma}) > \delta^S(\underline{\gamma})$. Proposition 7 demonstrates that a planner constrained to data regulation imposes a positive information tax. The subsidy in Equation (A59) extends this logic further. Since the economy's factor supply is fixed, these subsidies—being smaller for information-producing firms—implicitly tax information production. Yet, their proportionality to firm size ensures that firms' employment choices also reflect their contribution to social surplus. In particular, since $\delta^S(\bar{\gamma})/\delta^R(\bar{\gamma}) < \delta^S(\underline{\gamma})/\delta^R(\underline{\gamma})$, the social return to information (and to employment) within informed firms is lower than its private counterpart. Hence, it is straightforward to show that both information production and the relative size of information-producing vs non-producing firms declines after the intervention.

Second, consider the case where information production about demand is socially destructive, i.e., $\delta^S(\bar{\gamma}) < \delta^S(\underline{\gamma})$. Proposition 8 demonstrates that a planner limited to data regulation would garble firms' information about consumer tastes, reducing the share of H-type consumers faced by firms and thereby the likelihood of socially destructive rent extraction. The subsidy in Equation (A59) achieves a similar effect but, instead, by discouraging firms from customizing their products to consumer tastes. That is, firms, recognizing that post-subsidy profits are higher when facing a lower share of H-type consumers, choose to produce the variety types that, paradoxically, are *less likely* to match consumer preferences. $\square$

D Model Validation and Quantification

D.1 Sectoral Misallocation

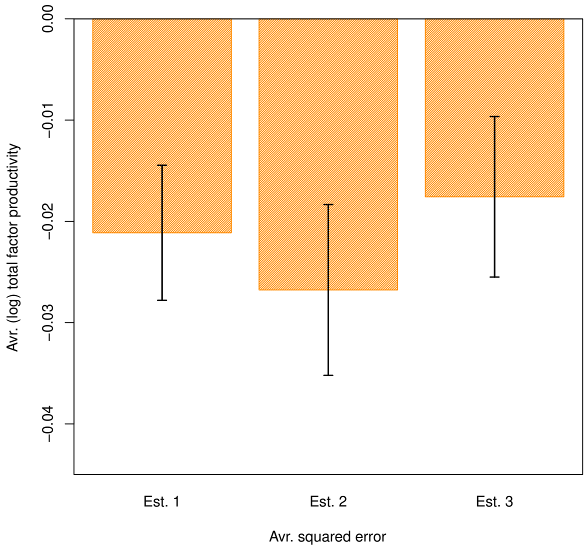
We define sectors by their four-digit NAICS industry classification. Building on the framework developed by Hsieh and Klenow (2009) and Gopinath *et al.* (2017), we compute our measures assuming a Cobb-Douglas production technology and monopolistic competition with CES demand. The profit-maximizing choice of an input for firm $i = \{1, 2, ..., N_s\}$ in sector $s = \{1, 2, ..., S\}$ at time $t = \{1, 2, ...\}$, thus, equates its marginal revenue product with its (sector-specific) cost. We assume the presence of two factors of productions, capital and labor. As a baseline and for comparability with our model below, we set the labor share α equal to 2/3, corresponding to the average labor share in the U.S. Our measures of misallocation are, however, not affected by the assumption that α is common across sectors, as these measures exploit within-sector variation of firm-level outcomes. Following the terminology in Foster *et al.* (2008), we define *revenue-based total factor productivity* (TFPR) as revenue divided by output net of firm total factor productivity (TFP).[41] The *marginal revenue product of labor and capital* (MRPN and MPRK, respectively) are, by contrast, defined as revenue divided by labor and capital employed by the firm, respectively. We take revenue, labor, and capital stock measures from the I/B/E/S-Compustat sample (Appendix A.1). Panel a in Figure ?? reports the average cross-sectional dispersion in log(MRPN), log(MRPK), and log(TFPR).[42] We report these estimates separately for accurate and inaccurate firms. We define "a good forecasting" firm as one that (i) is below the median in terms of the mean-squared-error of one-year-ahead log-revenue forecast; and (ii) one for which we have at least five observations.

[41] The production technology used by firm i is $y_{i,s,t} = A_{i,s,t} \cdot l^{\alpha}_{i,s,t} \cdot k^{1-\alpha}_{i,s,t}$, $\alpha \in (0,1)$, where $y_{i,s,t}$ is firm output, $l_{i,s,t}$ and $k_{i,s,t}$ the amount of labor and capital employed, respectively, and $A_{i,s,t}$ is firm total factor productivity. Let $p_{i,s,t}$ be the firm-specific product price. Then *revenue-based total factor productivity* is defined as: $\text{TFP}R_{i,s,t} \equiv \frac{p_{i,s,t} \cdot y_{i,s,t}}{l^{\alpha}_{i,s,t} \cdot k^{1-\alpha}_{i,s,t}}$. The marginal revenue product of labor and capital are, by contrast: $\text{MRPN}_{i,s,t} \equiv \kappa_L \cdot \frac{p_{i,s,t} \cdot y_{i,s,t}}{l_{i,s,t}}$ and $\text{MRPK}_{i,s,t} \equiv \kappa_k \cdot \frac{p_{i,s,t} \cdot y_{i,s,t}}{k_{i,s,t}}$, where $\kappa_L \in \mathbb{R}_+$ and $\kappa_K \in \mathbb{R}_+$ are common constants that depend on the elasticity of substitution and the labor share and capital share, respectively.

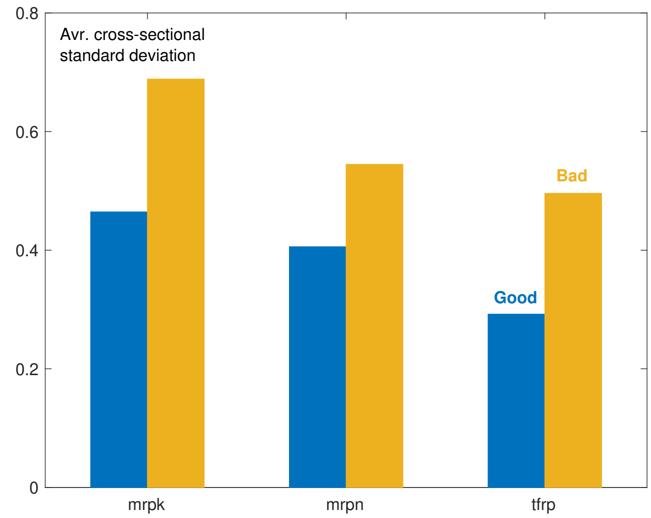
[42] We compute cross-sectional dispersion measures in two steps. First, we compute the standard deviation across firms i in a given sector s and year t. Second, for each year, we measure dispersion for the whole economy as the weighted average of dispersions across sectors. We give each sector a time-invariant weight equal to its average share in overall employment.

D.2 Qualitative Validation

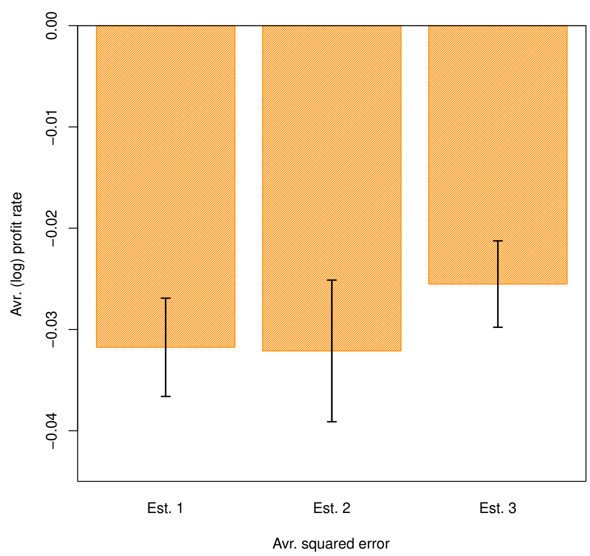
Figure D.1: Outcomes and accuracy



Panel (a): tfp-accuracy relationship



Panel b: misallocation

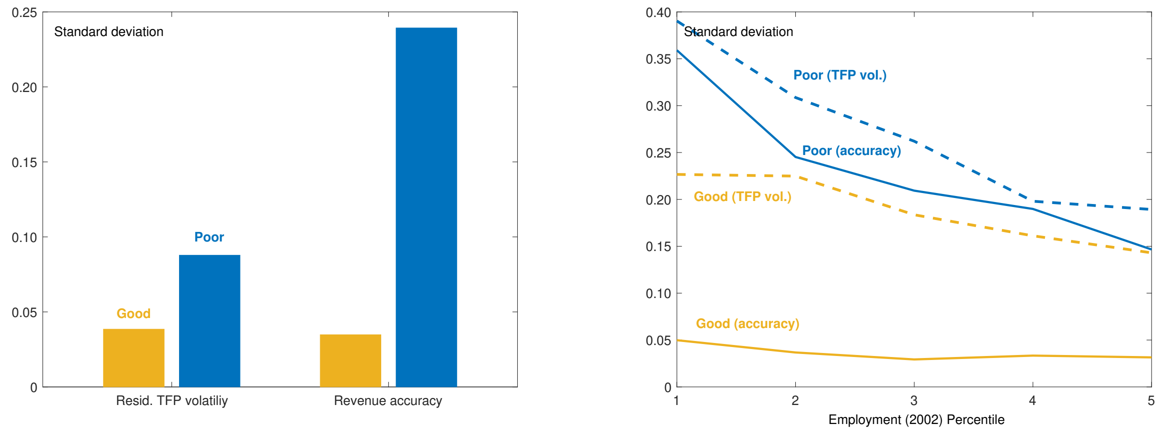


Panel (c): profit-accuracy relationship

Note: Panel (a) plots the coefficient from a regression of average firm (log-) total factor productivity on the mean-squared-error of one-year-ahead (log-)revenue forecasts (Est. 1) for the I/B/E/S-Compustat sample. The second column controls for firm age and sector fixed effects (Est. 2), while the third column trims TFP outlier observations at the 1 percent level (Est. 3). Panel (b) shows the average cross-sectional dispersion (standard deviation) in mrpn $\equiv \log(\text{MRPN})$, mrpk, and tfpr. Sectors are defined by their four-digit NAICS industry classification, and are weighted by their average share in overall employment. We define a "Good" firm as one that (i) is below the median in terms of the mean-squared-error of log-revenue forecasts; and (ii) one for which we have at least four observations. We compute $\text{tfpr}_j = 1/3 \cdot \text{mrpk}_j + 2/3 \cdot \text{mrpn}_j$. Panel (c) plots the results from analogous estimates to those in Panel (a) of the average (log-)profit rate for an individual firm on its mean-squared-error and controls. Whisker intervals correspond to one-standard deviation robust (clustered) standard errors. Sample: 2002-2022.

D.3 Auxiliary Model Validation

Figure D.2: Forecast accuracy and productivity volatility



Panel (a): accuracy relationship Panel (b): size quintiles

Notes: Panel (a) showcases the difference "Good" and "Poor" forecasting firms residualized (log-)tfp volatility, controlling for firm size, time, and and sector (NAICS-4) fixed effects. We define a "Good" forecasting firm as one that is below the 20th percentile of the mean-squared error distribution of one-year-ahead (log-) revenue forecasts. A "Poor" forecasting firm is one that is above the 80th percentile. Panel (b) shows the difference within each size quintile. Sample: 2002–2022 I/B/E/S-Compustat merger, described in Appendix A.1.

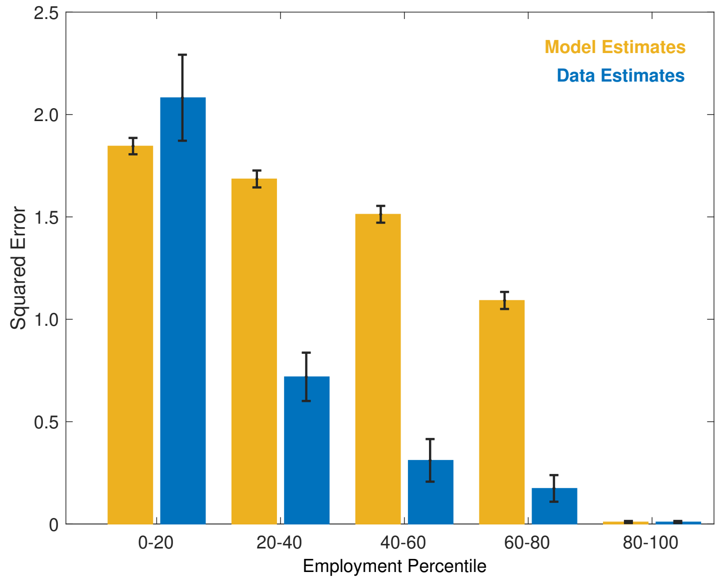
D.4 Model Parametrization

Table D.1: Model parameters

Parameters	Value
Externally calibrated parameters:	
Frisch elasticity (ψ)	0.00
Labor endowment (N)	1.00
Internally calibrated parameters:	
Variance of ex-ante log-productivity (τ_{μ}^{-1})	1/100
Variance of log-productivity shock (τ_{v}^{-1})	1/8
Symmetric household demand shifter ($\hat{\delta}$)	0.034
Accuracy of low productivity information ($\underline{\tau}_{\nu}$)	17.0
Accuracy of high productivity information ($\bar{\tau}_{\nu}$)	620.0
Accuracy of low demand information ($\underline{\tau}_{\nu}$)	0.50
Accuracy of high demand information ($\bar{\tau}_{\nu}$)	0.86
Fixed cost of information (χ)	0.14
Share of information firms ($1 - \Phi(z^{\star})$)	0.10

D.5 Quantitative Validation

Figure D.3: Accuracy Across the Size Distribution



Note: The figure shows the estimated relationship between squared normalized log. errors and firm size (quintiles of the initial employment distribution). We estimate this relationship both in the I/B/E/S-Compustat data and in the calibrated model (see also Section 2). The bars labelled data further control for sector and time fixed effects (Column 3 in Table I). Whisker intervals correspond to one-standard deviation robust (clustered) standard errors. Sample: 2002-2022.

D.6 The Extended Model

We augment the rent-extracting economy with capital and variety accumulation. To do so, we make four changes to the model. First, we assume household preferences are defined over consumption streams over time, $\{C_t^i\}$, and can be characterized by the utility function:

$$\mathcal{U}^i = \sum_{t=0}^{\infty} \beta^t \cdot \left[\log\left(C_t^i\right)\right], \tag{A60}$$

where $\beta \in (0, 1)$ and C_t is the consumption aggregator defined by Equation (9) over consumptions of varieties in every period. Second, we assume that each variety j at time t is produced as follows: the monopolistic firm j chooses the type x_{jt} and quantity y_{jt} of its variety to produce, according to technology:

$$y_{jt} = A_{jt} \cdot k_{jt}^{\alpha} \cdot n_{jt}^{1-\alpha}, \tag{A61}$$

where $\alpha \in (0, 1)$ and k_{jt} denotes firm j's use of the capital input at time t. Capital depreciates at rate $\rho \in (0, 1)$ and can be rented from households in a competitive rental market at rate

r_t. Third, in this two-factor economy, we suppose that information production requires the allocation of χ units of the numeraire good to it. Finally, we assume that creation of varieties requires f units of the numeraire, but that varieties become obsolete at rate $\eta \in (0,1)$ in every period. The rest of the setup is the same as before. Namely, information production yields the firm signals about productivity and demand, which are now also assumed to be iid over time. We also assume that consumer preference shocks are iid over time. Investments into capital, varieties, and information take one-period to materialize.

D.6.1 Steady State Equilibrium

We focus on the steady state equilibrium of this economy.

Firm-level choices. At *Stage 3*, the solution to the optimal mechanism is the same as before, implying that when making its choices (x_j, n_j, k_j, ι_j) a firm faces the revenue-based demand shifter δ_j^R. At *Stage 2*, the firms will choose to set $x_j = s_j^\omega$, and labor and capital as follows:

$$n_j = \frac{1-\alpha}{w} \cdot \frac{w^{1-\alpha} \cdot r^\alpha}{(1-\alpha)^{1-\alpha} \cdot \alpha^\alpha} \cdot \exp^{(\theta-1)\cdot\mu_j} \cdot g^R(\boldsymbol{\tau}_j)^{\theta-1} \cdot \Omega, \tag{A62}$$

and

$$k_j = \frac{\alpha}{r} \cdot \frac{w^{1-\alpha} \cdot r^\alpha}{(1-\alpha)^{1-\alpha} \cdot \alpha^\alpha} \cdot \exp^{(\theta-1)\cdot\mu_j} \cdot g^R(\boldsymbol{\tau}_j)^{\theta-1} \cdot \Omega, \tag{A63}$$

where the market size faced by firms is now defined as:

$$\Omega \equiv C \cdot \left(\frac{\theta}{\theta-1} \cdot \frac{w^{1-\alpha} \cdot r^\alpha}{(1-\alpha)^{1-\alpha} \cdot \alpha^\alpha}\right)^{-\theta} \tag{A64}$$

and $g^R(\cdot)$ is the revenue-based information shifter defined in the main text. At *Stage 1*, firm j's expected profits for a given information choice can be expressed as:

$$\mathbb{E}[\pi_j | \mu_j, \boldsymbol{\tau}_j] = \frac{1}{\theta-1} \cdot \exp^{(\theta-1)\cdot\mu_j} \cdot g^R(\boldsymbol{\tau}_j)^{\theta-1} \cdot \Omega \cdot \frac{w^{1-\alpha} \cdot r^\alpha}{(1-\alpha)^{1-\alpha} \cdot \alpha^\alpha}, \tag{A65}$$

implying that a firm produces information if and only if

$$\beta \cdot \frac{1}{\theta-1} \cdot \exp^{(\theta-1)\cdot\mu_j} \cdot \left(g^R(\bar{\boldsymbol{\tau}})^{\theta-1} - g^R(\underline{\tau})^{\theta-1}\right) \cdot \Omega \geq \frac{\chi}{\frac{w^{1-\alpha} \cdot r^\alpha}{(1-\alpha)^{1-\alpha} \cdot \alpha^\alpha}}. \tag{A66}$$

Aggregate Implications. The aggregate TFP of this two-factor economy is given by:

$$\mathcal{A}^\star = \mathcal{E}(\mu^\star) \cdot \mathcal{A}\left(\mu^\star, g^R, M\right) \tag{A67}$$

where:

$$\mathcal{A}\left(\mu^{\star}, g^{R}, M\right) = M^{\frac{1}{\theta-1}} \cdot \exp^{\frac{\theta-1}{2} \cdot \frac{1}{\tau_{\mu}}} \cdot \left(\xi\left(\mu^{\star}\right) \cdot g^{R}\left(\bar{\boldsymbol{\tau}}\right)^{\theta-1} + \left(1 - \xi\left(\mu^{\star}\right)\right) \cdot g^{R}\left(\underline{\boldsymbol{\tau}}\right)^{\theta-1}\right)^{\frac{1}{\theta-1}}, \quad \text{(A68)}$$

and where $\xi(\cdot)$ is given by Lemma 2. Thus, due to a love-of-variety effect, the mass of varieties, M, also enters into the economy's TFP. To ensure that consumption growth is zero, the rate of return on capital must satisfy:

$$r = \beta^{-1} - 1 + \delta. \quad \text{(A69)}$$

The wage rate must in turn be such that the labor market clears:

$$N = \mathcal{A}\left(\mu^{\star}, g^{R}, M\right)^{\theta-1} \cdot \Omega \cdot \left(\frac{r}{w} \cdot \frac{1-\alpha}{\alpha}\right)^{\alpha}. \quad \text{(A70)}$$

where the market size Ω is now defined in Equation (A64). Aggregation of individual capital holdings implies that the aggregate capital stock is given by:

$$K = \mathcal{A}\left(\mu^{\star}, g^{R}, M\right)^{\theta-1} \cdot \Omega \cdot \left(\frac{r}{w} \cdot \frac{1-\alpha}{\alpha}\right)^{\alpha-1}, \quad \text{(A71)}$$

while aggregate consumption equals:

$$C = \mathcal{A}^{\star} \cdot K^{\alpha} \cdot N^{1-\alpha} - \delta \cdot K - M \cdot \left[\chi \cdot \Phi\left(-\mu^{\star} \cdot \sqrt{\tau_{\mu}}\right) + \eta \cdot f\right], \quad \text{(A72)}$$

which we note captures that the costs of information production, and of capital and variety creation require expenditure of the numeraire good. Finally, in equilibrium, as all potential entrant varieties are ex-ante identical, it follows that expected profits (including entry costs) must equal to zero:

$$\chi \cdot \Phi\left(-\mu^{\star} \cdot \sqrt{\tau_{\mu}}\right) + (1 - \beta \cdot (1-\eta)) \cdot f = \frac{1}{\theta-1} \cdot \frac{\mathcal{A}\left(\mu^{\star}, g^{R}, M\right)^{\theta-1}}{M} \cdot \beta \cdot \Omega \cdot \frac{w^{1-\alpha} \cdot r^{\alpha}}{(1-\alpha)^{1-\alpha} \cdot \alpha^{\alpha}}. \quad \text{(A73)}$$

Equations (A62) through (A73) fully characterize the steady state of this extended economy.

D.6.2 Extended Calibration

We set the fixed cost of entry, f, so that the mass of firms in the steady-state of the model equals one (i.e., the mass in the rent-extracting and baseline economy). We set the discount factor (β), the capital depreciation rate (ρ), the capital share (α), and the exit rate (η) to standard values used in the literature (0.96, 0.02, 0.33, 0.02, respectively). The rest of the parameters are calibrated in the same manner as in the rent-extracting and baseline economy.

D.6.3 Extension and Decomposition

Table D.2: Extended model: decomposition of the rise in TFP

Model	Overall (%)	Scale	Product	Pricing	Variety	$\underline{\gamma}$	$\bar{\gamma}$
Best case	6.9	5.0	2.3	0.0	-0.4	0.00	1.00
Worst case	2.7	5.0	2.3	-1.9	-2.6	0.70	0.85

Note: The table decomposes the rise in TFP in Figure 8 into its four constituent channels: (i) scale, (ii) product design, (iii) pricing; and (iv) variety generation. The table does so for the "best case" and for the "worst case" economy identified as in the main text.

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