General-Purpose Technology and Firm Production: Evidence from Broadband Internet *

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Abstract

We study broadband internet as a general-purpose, *multi-dimensional* technology shock to firm production that simultaneously relaxes frictions in external market access, internal firm operations, and input usage. Theoretically, we show that since these channels interact, the implications for *how* firms grow after adoption (e.g., capital vs labor, skill vs scale) are ambiguous. Using detailed production data and novel measures of firm-level ICT usage for a long panel of Colombian manufacturing firms, we employ an instrumental variables strategy to identify the causal effects of broadband adoption. Internally, firms expand digital communication, scale up investment in capital, and increase employment of frontline production workers through online hiring and training. Externally, broadband expands market access by increasing exports, online transactions, and participation in e-commerce. Quantitative estimates indicate that improved market access and lower unit-costs of production contribute roughly equally to firm-level output growth, while input adjustments reflect the interaction of scale effects, substitution patterns, and equilibrium price responses. In the aggregate, broadband accounts for approximately 7% of manufacturing output and 1.3% of real income, and ignoring any single dimension of firm growth understates its aggregate economic impact.

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1 Introduction

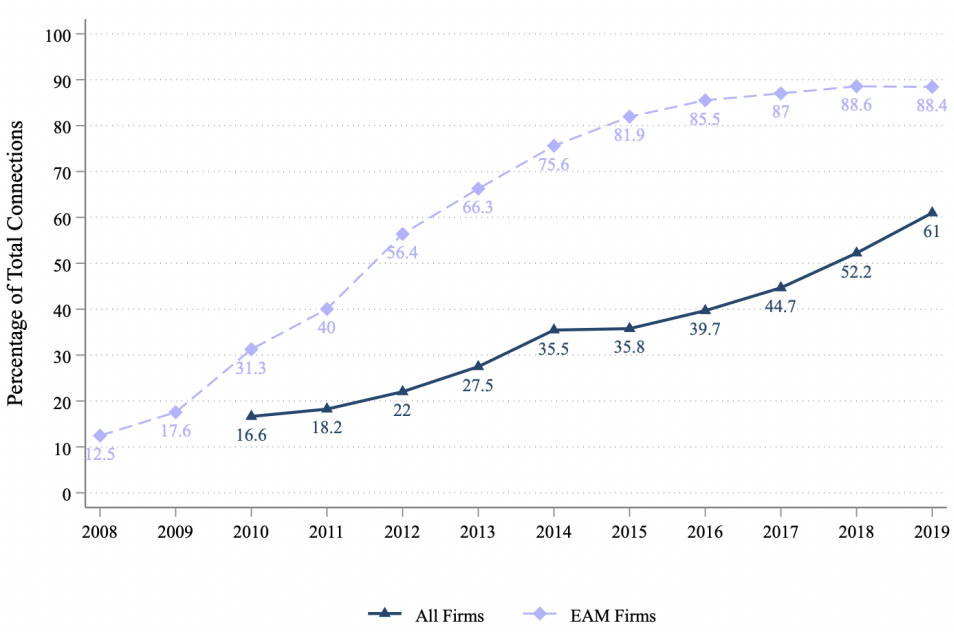
The past two decades have seen a rapid adoption of broadband internet across developing economies, reshaping (among other things) how firms produce, organize, and interact with markets. However, technological change such as the internet (and artificial intelligence more recently) is rarely a *single* "shock" to firm productivity. On the one hand, it can lower the costs of finding and transacting with customers, thus improving market access. On the other, it can lower per-unit production costs, for example, by providing access to cheaper and better inputs, reducing monitoring and coordination costs, etc. These forces are not additive: if the internet relaxes multiple constraints at once, the resulting changes in scale, input mix, and production depend on substitution possibilities inside the production technology and on equilibrium price responses in factor markets. As a result, even basic predictions (e.g., whether employment rises or falls, whether firms become more or less capital-intensive, etc.) are ambiguous ex-ante.

Existing evidence on the impact of internet adoption within firms largely draws from cross-country studies, or those in high-income ones, and shows that internet adoption primarily raises firm productivity and employment (Hjort and Poulsen, 2019; Cariolle et al., 2018; Cusolito et al., 2020; Bhuller et al., 2023; Hjort and Tian, 2021). However, understanding the economic impact of internet adoption more comprehensively requires going beyond cursory measures of firm performance and taking a more holistic approach that can simultaneously: (i) measure the distinct margins through which broadband internet operates; (ii) identify their causal effects on firm choices; and (iii) quantify their relative importance in a general-equilibrium framework.

This paper provides such an account in the Colombian context. We study the adoption of broadband internet by manufacturing firms between 2008 and 2019, a period when high-speed internet diffusion accelerated sharply — from around 15% in 2010, to over 60% a decade later (see Figure 1).[1] Colombia provides an ideal setting because broadband expansion was rapid, but heterogeneous across space, and accompanied by substantial public and private investment in digital infrastructure. It also collects unusually rich firm-level data that allow us to move beyond conventional outcomes of firm performance and instead open the black box of adoption to see: how firms change their external, market-facing behavior; how they reorganize production internally; and which specific inputs expand or contract when broadband is adopted.

[1] In our sample of formal manufacturing firms, the increase in adoption was even more stark: from 17% to 88% over the same time period.

Figure 1: Broadband Internet Adoption in Colombia



Notes: The above figures plots the percentage of high-speed broadband internet adoption in Colombia between 2008-2019. The sample consists of all connections (triangles) and formal manufacturing firms in our sample (diamonds).

We first begin, however, by developing a general theoretical framework (see Section 2) where broadband adoption shifts firm outcomes through three main channels: (i) improved market access that scales demand; (ii) lower internal frictions that lower effective input costs and raise operational efficiency; and (iii) general equilibrium adjustments that operate through incomes and factor prices. A key conceptual implication of the theory is that broadband is inherently a *multi-dimensional* shock to firm production. It simultaneously relaxes external (e.g., customer reach, transaction costs, etc.) and internal constraints (e.g., hiring, training, monitoring, and coordination) in production, which further interact through a general production technology. The framework therefore clarifies why observed reorganization of inputs are not mechanical implications of technology adoption, but an equilibrium outcome of scale effects, substitution patterns across inputs, and wage and price responses.

We then take this framework to the data using a long panel from Colombia's Annual Manufacturing Survey (EAM) spanning over a decade (2008-19). The EAM is an annual census of formal manufacturing firms and is particularly valuable for our purpose because it records detailed outcomes of firm production — sales, value added, production costs, employment by occupation and contract type, investment by capital category, and interna-

tional trade. In addition, it includes a dedicated ICT module that reports not only whether firms have broadband, but also how they use the internet across a wide range of activities. This feature is central to our exercise, as it lets us directly observe how broadband-enabled changes operate through both external market access (e.g., websites, customer support, e-commerce, etc.) and internal firm operations (e.g., online hiring and training of workers, using internet-based tools for communication and workflow, etc.).

Identifying causal effects is challenging because broadband adoption is an endogenous choice that may be correlated with firm-specific growth prospects. We address this concern in three ways. First, we estimate specifications with firm fixed effects and rich region-by-year and four-digit industry-by-year fixed effects, absorbing time-invariant firm heterogeneity and local and sectoral time-varying shocks. Second, we implement an instrumental variables strategy that exploits plausibly exogenous supply-side expansion in broadband availability interacted with lagged (leave-one-out) industry–region firm exposure to internet usage. Third, we examine dynamic event-study patterns using recent econometric estimators for staggered treatment timing (Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2024; Dube et al., 2023; Malgouyres et al., 2019) and show that key outcomes do not exhibit differential pre-trends prior to adoption, while diverging sharply afterward (see Appendix C.3). Together, these approaches support the interpretation that the estimated post-adoption firm changes reflect the causal impact of adopting broadband.

The reduced-form evidence, presented in Section 4, shows that broadband generates large, sustained improvements in firm performance as measured by real output, sales, and real value added. The key contribution, however, is not simply documenting firm growth, but characterizing the reorganization of production that accompanies it. Broadband adopters expand employment by roughly 17 workers cumulatively (about 3 workers per year on average), primarily through more frontline production labor. On the other hand, professional and technical employment declines, and managerial employment changes little. At the same time, firms increase investment across multiple forms of capital — computers and ICT equipment, machinery, and transportation. This indicates that broadband adoption (in our context) is consistent with a model of scaling operational capacity (Bloom et al., 2014; Bartik et al., 2023) as opposed to complementing non-routine cognitive labor (Autor et al., 2003; Akerman et al., 2015).

Broadband adoption also expands market reach in a way that is informative about underlying mechanisms. Adoption increases exporting on both the extensive and intensive

margins, while having little effect on imports. This asymmetry suggests that broadband primarily lowers demand-side access barriers rather than simply reducing frictions in sourcing inputs. Finally, the ICT module (discussed in Section 4.4) is key to providing *direct* evidence of the *multi-dimensional* channels emphasized by the theory. After adopting broadband, firms are substantially more likely to adopt external digital practices — maintaining websites, providing online customer service, sending and receiving orders digitally, and participating in e-commerce. They also adopt internal digital practices — using the internet to hire and train workers and deploying internet-based applications and VoIP tools (e.g., Skype) that support coordination and communication within the firm. These internal operational changes help rationalize how firms scale production employment and capital without proportional expansion in managerial and administrative layers.

The above discussion establishes that broadband changes firm behavior along many margins, but it cannot answer three central quantitative questions: which channels account for most of the gains? how much is attenuated by equilibrium price responses? and how important are the implications for aggregate output and welfare? To address these, we build and estimate a quantitative heterogeneous-firm model in Section 5 that is explicitly designed to capture the multi-dimensional nature of broadband as a joint shock to market access and input-specific frictions. Firms produce using a flexible variable-elasticity-of-substitution (VES) technology that allows flexible substitution and complementarity patterns across inputs. This flexibility is essential for matching the empirical patterns discussed previously, which are inconsistent with standard Cobb-Douglas restrictions on constant cost shares, or with CES restrictions on the constant elasticity of substitution across inputs.

The model provides a transparent quantitative decomposition of the channels that drive firm expansion with broadband adoption. First, as discussed in Section 6, market access and unit-cost reductions can each explain around 35-40% of expansion in firm output, with equilibrium factor prices accounting for the remaining. Turning to inputs, the importance of channels is heterogeneous. Scale effects and lower input frictions explain the expansion in frontline production workers. In contrast, input frictions matter little for other inputs, where the positive scale effects are dampened by (negative) substitution patterns towards frontline production. In all cases, higher factor prices in equilibrium further attenuate these partial-equilibrium gains. In other words, this decomposition illustrates, quantitatively, that the impact of broadband is indeed multi-dimensional and heterogeneous across inputs. Finally, at the aggregate level, adoption raises manufacturing output by roughly 7% and real income (our measure of welfare) by 1.3%, and shutting

down only one channel — either market access or input-specific frictions — substantially underestimates these gains.

To summarize, these results clearly demonstrate the impact of broadband not as a one-dimensional productivity shifter, but as a general-purpose, multi-dimensional technology that relaxes multiple constraints within a firm at once, thus changing what they can sell, how they produce, and how they organize to scale.

Our paper contributes to two strands of the literature. A long tradition emphasizes that major technologies function as general-purpose innovations whose effects depend on complementarities with downstream organizational and process change (Bresnahan and Trajtenberg, 1995). In firm settings, this perspective motivates models and evidence in which adoption alters not only efficiency but also the internal allocation of tasks and the structure of decision-making (Garicano, 2000; Garicano and Rossi-Hansberg, 2006). Complementing these theory approaches, classic empirical work shows that IT tends to be valuable precisely because it is bundled with workplace reorganization and changes in skill demand, rather than operating as a stand-alone input (Bresnahan et al., 2002). This paper contributes to that agenda by providing a unified theoretical framework and causal reduced-form analysis using detailed firm-level data to show that broadband adoption is an empirically salient example of multi-dimensional technological change..

A growing empirical literature specifically studies broadband and internet technologies using plausibly exogenous rollout variation and documents economically meaningful impacts on labor markets and firm performance (Hjort and Poulsen, 2019; Cusolito et al., 2020; Bhuller et al., 2023; DeStefano et al., 2023). Much of this work, however, necessarily treats mechanisms as latent — inferring channels from reduced-form outcomes such as employment, wages, or productivity. Related work emphasizes that the economic payoffs to internet technologies depend on how they are adopted and used, and that observed heterogeneity in outcomes reflects differences in applications and complementarities (Forman et al., 2012; Bloom et al., 2014). This paper advances this literature by measuring mechanisms directly at the firm level, thus separating external, market-facing uses of broadband from internal, operational uses. In addition, it provides a unified theory that quantifies the importance of these channels in firm growth and aggregate output and welfare.

The remainder of the paper is structured as follows. Section 2 develops a general theoretical model, while Section 3 discusses the institutional context and empirical strategy.

Section 4 presents the reduced-form empirical results. Section 5 then develops a structural model that we estimate and quantify in Section 6. 7 offers a short conclusion.

2 A General Framework of ICT Adoption

2.1 Setup

Consumer Demand. Consider a continuum of firms indexed by productivity $z \in \mathbb{R}_+$, each producing a differentiated variety under monopolistic competition. Each firm faces a general inverse demand curve, with corresponding firm revenue given by:

$$p = \lambda_x p(q; \mathcal{I}), \qquad \mathcal{R}(q; \mathcal{I}) = \lambda_x p(q; \mathcal{I})\, q \tag{1}$$

where q is its own quantity and I is aggregate real income. $\mathcal{R}$ is continuous, increasing, and strictly concave in q. This general specification nests commonly used demand systems (e.g., CES, Cobb-Douglas, etc.) as special cases.

The parameter $\lambda_x \in [0, 1]$ acts like a demand-shifter that captures a firm's "market-access". It can offer several interpretations related to a measure of consumers who a firm can access (extensive margin), or the probability that firm is successfully matched with a consumer in an environment with search and matching frictions, or the fraction of potential transactions that convert into effective delivered demand net of informational, coordination, or transaction costs. Under any of these microfoundations, a higher λ_x scales firm-level demand.

Internet adoption provides a natural and compelling mechanism through which λ_x may increase. High-speed internet access reduces a range of market-access frictions that firms face, including search and discovery costs, geographic barriers, and coordination and transaction costs. Firms with broadband connectivity can advertise and list products online, participate in digital marketplaces, communicate more effectively with buyers and suppliers, and reach consumers outside their immediate local market. In business-to-business contexts, broadband facilitates participation in procurement platforms, improves reliability in order processing, and reduces delays associated with information exchange.

Production. Output is produced according to a general production function

$$y = F(z, \boldsymbol{\ell}),$$

where $\boldsymbol{\ell} = (l_1, \ldots, l_n)^\top$ is a vector of inputs, F is increasing and weakly concave in each input, and $F_z > 0$. This general formulation allows for an arbitrary partition of inputs, e.g., between production and administrative inputs, or between capital and labor, etc. It therefore allows internet adoption to affect a subset of inputs that may be technologically complementary or substitutable with others. In other words, we remain agnostic about how ICT capital operates in production, letting the data discipline those interactions later.

Input Prices and Frictions. Let $\mathbf{w} = (w_1, \ldots, w_n)^\top$ denote the vector of factor prices in the economy. In addition, let firms face additional per-unit frictions in employing input i, summarized by the vector $\boldsymbol{\lambda}(B) = \{\lambda_i(B)\}_{i \in 1,\ldots,n\}}$. These capture technological or organizational frictions faced by a firm and may potentially change depending on whether a firm adopts internet or not, denoted by their adoption status $B \in \{0, 1\}$. For example, for labor inputs (L), $\lambda_L(B)$ can represent (in a reduced-form way) search and matching costs for hiring workers, or monitoring frictions in managing them, etc. that broadband can help reduce. This implies a vector of *effective* input prices given by:

$$\widetilde{\mathbf{w}}(B) = \boldsymbol{\lambda}(B) \circ \mathbf{w}$$

where $\circ$ denotes element-wise multiplication.

ICT-Biased Technical Change. As is standard in these models, the duality of firm production and optimization implies that firms equate marginal costs and revenues. This means that (in a reduced-form way) changes in $\{\lambda_i, \lambda_x\}$ due to ICT adoption can capture changes in *both* costs and productivity (e.g., ICT-based technical change). In the absence of detailed task-level data on inputs, these are indistinguishable in the theory and data. For the rest of the paper, we therefore choose not to specifically add a separate ICT productivity channel, though the framework can easily be extended to accommodate one.

Summary. The above environment provides a very general framework where internet adoption can impact firm production through: (i) a *demand-side* channel or market access (λ_x); (ii) an *input-side* channel through frictions (λ_i). Since these channels interact inside a fully general production function, the model can explain not only *whether* firms grow after adopting broadband, but also *how* they can grow — through scale expansion, input reallocation, or both.

2.2 Input Choices

We now characterize the firm's optimal input choices. Given the effective input prices $\widetilde{\mathbf{w}}(B)$ and firm productivity z, the minimum cost of producing q units is given by:

$$C\big(q;\,\widetilde{\mathbf{w}}(B),z\big)=\min_{\boldsymbol{\ell}\geq 0}\Big\{\widetilde{\mathbf{w}}(B)^{\top}\boldsymbol{\ell}:\;\; q\leq F\big(z,\boldsymbol{\ell}\big)\Big\}. \tag{2}$$

Under the regularity assumptions on F, C is increasing and weakly convex in q, and increasing in each component of $\widetilde{\mathbf{w}}$. By Shephard's Lemma, the *Hicksian* (cost-minimizing) input demands are given by:

$$\mathbf{h}(q,\widetilde{\mathbf{w}})=\nabla_{\widetilde{\mathbf{w}}}C(q,\widetilde{\mathbf{w}}),\qquad h_i=\frac{\partial C}{\partial\widetilde{w}_i}. \tag{3}$$

Profit maximization implies a firm chooses q to equate marginal revenues and costs, i.e.,

$$\lambda_x\,\mathcal{R}_q(q^*;\mathcal{I})=C_q\big(q^*;\widetilde{\mathbf{w}}(B),z\big), \tag{4}$$

with the second-order condition $\lambda_x\,\mathcal{R}_{qq}-C_{qq}<0$.

2.3 Impact of Internet Adoption on Firm Production

We now examine the impact of internet adoption on firm output (Proposition 1) and inputs (Proposition 2). Broadly, we show in Proposition 1 that while adoption increases firm output, equilibrium changes may dampen its effects. Proposition 2 then shows that *how* firms adjust input choices, however, is ambiguous and largely depends on how input frictions change, the substitutability and complementarity across inputs, and equilibrium changes in input prices.

Proposition 1. *The impact of internet adoption on firm output is given by:*

$$\frac{dq^*}{dB}=\frac{\underbrace{\lambda_x'(B)\,\mathcal{R}_q}_{\triangle\text{Market Access}}\;-\;\underbrace{\nabla_{\widetilde{\mathbf{w}}}C_q^{\top}\frac{d\widetilde{\mathbf{w}}}{dB}}_{\triangle\text{Effective Input Prices}}\;+\;\underbrace{\lambda_x\,\mathcal{R}_{q\mathcal{I}}\frac{d\mathcal{I}}{dB}}_{\triangle\text{G.E. Demand}}}{C_{qq}-(1-\tau_x)\,\mathcal{R}_{qq}}, \tag{5}$$

The change in the vector of effective input prices is given by:

$$\frac{d\widetilde{\mathbf{w}}}{dB}=\underbrace{\boldsymbol{\lambda}'(B)diag(\mathbf{w})}_{\triangle\text{Input Frictions}}+\;\underbrace{diag(\boldsymbol{\lambda})\,\frac{d\mathbf{w}}{dB}}_{\triangle\text{ G.E. Input Prices}} \tag{6}$$

See Appendix B.1 for the mathematical proof. Equations (5) and (6) shows that internet adoption impacts firm production through three channels: (i) a *demand-side channel* through better market access ($\lambda'_x(B) > 0$) that raises (effective) marginal revenue; (ii) lowering input frictions that lower marginal costs ($\lambda'_i(B) < 0$); and (iii) changes operating in general equilibrium through input prices ($\frac{\partial w_i}{\partial B}$) and real income ($\frac{d\mathcal{I}}{dB}$).

Partial and General Equilibrium Impacts: The first two channels unambiguously increase firm output. However, the effects operating through general equilibrium are ambiguous. For example, suppose internet adoption lowers frictions in hiring workers, $\lambda'_L(B) < 0$. In partial equilibrium, output rises because labor becomes cheaper and firms demand more of it. However, if this increases worker wages in equilibrium, it can dampen the impact on output through lowering effective input prices ($d\widetilde{\mathbf{w}}/dB$). Furthermore, internet adoption can increase aggregate real income — through both higher factor payments and lower aggregate prices — increasing output as well.

Proposition 2. *The change in demand for inputs can be given by:*

$$\frac{d\boldsymbol{\ell}^*}{dB} = \underbrace{\mathbf{h}_q \frac{dq^*}{dB}}_{\triangle \text{Scale Effect}} + \underbrace{\mathbf{H}_{\widetilde{\mathbf{w}}}}_{\text{Substitution Effect}} \left[\underbrace{\boldsymbol{\lambda}'(B) diag(\mathbf{w})}_{\triangle \text{Input Frictions}} + \underbrace{diag(\boldsymbol{\lambda}) \frac{d\mathbf{w}}{dB}}_{\triangle \text{ G.E. Input Prices}} \right] \tag{7}$$

where: (i) $\mathbf{h}(q^*, \widetilde{\mathbf{w}}, \Theta; B) = \nabla_{\widetilde{\mathbf{w}}} C$ *is the Hicksian demand for inputs given by Equation (3); (ii)* $\mathbf{H}_{\widetilde{\mathbf{w}}} = \nabla_{\widetilde{\mathbf{w}}} \mathbf{h} = \nabla^2_{\widetilde{\mathbf{w}}\widetilde{\mathbf{w}}} C$ *is the Hicksian (Slutsky) matrix, which is symmetric and negative semidefinite; and (iii) from Proposition 1, the change in the effective input price* $\frac{\partial \widetilde{\mathbf{w}}}{\partial B}$.

See Appendix B.2 for proof. Each component of Equation (7) clearly decomposes the channels through which internet adoption impacts input choices: (i) a *scale effect*, that comes from adoption raising optimal output ($dq^*/dB > 0$) and hence the demand for all inputs ($h_q > 0$); (ii) a change in the effective input prices (from Proposition 1); and (iii) a *substitution effect* driven by the composition of the Slutsky matrix $\mathbf{H}_{\widetilde{\mathbf{w}}}$. This captures how changes in effective prices of an input j impact the choice of input i.[2]

Both the propositions discussed above show the channels through which firms' production decisions can be impacted by internet adoption. Output is impacted by market access, input frictions, and equilibrium changes in input prices and incomes, whereas the input

[2]The Slutsky is matrix is negative semi-definite. The diagonal elements are (negative) own-price effects i.e., raising an input's own price (or friction) lowers its demand. The off-diagonal elements on the other hand are the cross-price effects that show whether inputs are complements ($H_{i\widetilde{p}_j} > 0$), or substitutes ($H_{i\widetilde{p}_j} < 0$).

choices are then driven by the scale and substitution effects. Together, they explain not only *whether* firms grow but also *how* they do it.

2.4 Interdependent Channels and The Role of Broadband Adoption

The model makes clear that broadband affects firm behavior not through a single friction, but through a combination of interdependent channels that govern both demand and input use. By relaxing market access frictions (λ_x), broadband adoption enables scale. Simultaneously, improvements in ICT capital productivity (θ_z) alter the tradeoff between ICT capital and managerial labor, while reductions in hiring frictions (λ_l and λ_s) lower the cost of adjusting the workforce, particularly toward payroll employees.

An important insight from the model is that these channels interact to impact production in ways that are not ex-ante obvious. For instance, higher ICT productivity pushes firms to substitute workers for capital, but if broadband lowers hiring costs as well, it may simultaneously increase labor demand. In addition, greater market access scales production and hence, demand for all inputs. The net effect on labor and capital is therefore ambiguous and depends on the joint distribution of these channels, in addition to factor prices and firm entry in equilibrium.

This motivates the need to examine the impact of broadband adoption on firm production empirically, which we do in Sections 3 and 4 below.

3 Data and Empirical Strategy

3.1 Annual Manufacturing Survey (EAM)

Our primary data is an (unbalanced) panel of 12,313 firms in Colombia's formal manufacturing sector over a 12 year period from 2008-2019. These data are collected from the *Encuesta Anual Manufacturera* (or EAM). EAM is a census of manufacturing firms in Colombia that employ at least 10 workers or have an output value that is established annually, which is increased based on the Producer Price Index (PPI). It gathers very detailed information about the production process of a firm such as employment, costs, assets, investment, output, intermediate materials, etc. Moreover, starting 2008, the EAM also collected information on ICT usage in a plant, which reports the type of internet connection (DSL, ADSL, Fiber Optic, etc.), number of workers who use the internet, and most importantly, why the firm uses internet. The ICT module captures detailed information

on whether a firm uses internet for email and communication, buying and selling goods online, engaging with government institutions, using apps (like Skype, etc.), online contracting as well as personnel training.

3.2 Supplementary Data

Apart from the EAM, we use other administrative data available from the Ministry of Information and Communication (MinTIC). MinTIC collects data at the municipality level every quarter on the number and type of internet connections (DSL, ADSL, fiber optic, Wifi, etc.), types of users (residential, businesses, government, etc.) and the number of service providers. Since the EAM covers the formal manufacturing sector, we use these data to validate the pattern of supply-side expansion and demand-adoption of high-speed internet across Colombia. We also use these data to construct the instrument (discussed in the next section).

3.3 Empirical Strategy

We now turn to our main empirical strategy, which aims to identify the causal effect of broadband internet adoption on firm performance, by comparing changes in outcomes before and after adoption across firms, while controlling for rich time-varying heterogeneity at the region and industry level. We construct a binary indicator $\mathbb{1}(\text{Broadband}_{it})$ that takes the value 1 in all years after firm i adopts broadband internet, and 0 otherwise.[3] We then estimate the following regression specification:

$$Y_{it} = \alpha_i + \alpha_{st} + \alpha_{jt} + \beta \mathbb{1}(\text{Broadband internet})_{it} + \varepsilon_{it} \tag{8}$$

where Y_{it} is an outcome of interest (such as sales, costs, etc.), α_i are firm fixed effects, α_{st} are region-year fixed effects, and α_{jt} are (4-digit) industry-year fixed effects. The combination of these fixed effects control for all time-invariant firm heterogeneity as well as sectoral or geographic changes over time. Put together, these can account for many common channels that might bias the OLS results. For example, if on average, larger, more productive firms are likely to adopt broadband, or if a particular region experiences an infrastructure expansion that increases both internet availability and firm productivity, or if there are shocks to sectoral output (such as trade) in ways correlated with adoption, these are accounted for by the firm, region-year, or industry-year fixed effects respectively.

That said, endogeneity concerns remain. Even with extensive fixed effects, broadband

[3] Broadband internet is defined as a fiber or wifi internet connection with a speed of at least 2 Mbps.

adoption may still be correlated with time-varying, firm-specific unobservables. For example, a firm anticipating growth may be more likely to upgrade its internet connection, which might create a risk of reverse causality. Similarly, measurement error in self-reported broadband usage could further attenuate OLS estimates toward zero. To address these concerns and obtain consistent causal estimates, we turn to an instrumental variables strategy described below.

Instrumental Variable Strategy

We construct an instrument that exploits variation in the supply-side availability of broadband interacted with lagged region-industry exposure to it. In other words, the instrument is an interaction between: (i) the (log) number of broadband providers in a region and year, Ln(Providers)$_{rt}$; and (ii) the lagged leave-one-out internet exposure in firms' industry and region, $\overline{\text{Exposure}}_{-i,jrt-1}$. Exposure is calculated as the lagged average internet speed (in Mbps) used by firms in 4-digit industry-region jr in year $t-1$ after excluding firm i.[4] This measure therefore captures both the extensive margin, and the intensive margin quality of internet usage by other firms in an industry-region. For a firm i operating in region r and industry j in year t, our instrument is therefore defined as: $Z_{i(jr)t} = \text{Ln Providers}_{rt} \times \overline{\text{Exposure}}_{-i,jrt-1}$.

This interaction captures two key forces shaping firm adoption of broadband internet. The first component captures supply-side variation: more broadband providers in a region can induce more adoption. One might be concerned about the endogenous expansion of providers across regions based on socio-economic factors in them. Apart from region-year fixed effects, projects were also approved under Colombia's national broadband expansion policy — the Proyecto Nacional de Fibra Óptica, which aimed to increase geographic coverage in broadband internet through public-private partnerships, generating spatial variation in providers across regions.[5]

The second component — lagged internet exposure at the region-industry level — reflects latent *firm* demand for adoption. In essence, in regions and industries where firms were already using the internet intensively, broadband availability is more likely to translate into adoption. Crucially, the inclusion of region-year and industry-year fixed effects ensures that identification comes from variation in this interaction, rather than level changes

[4]For firms that do not use any internet, we set this to zero.

[5]See details on PNFO here. Despite this plausibly exogenous expansion, the presence of more providers in a region would also impact consumers' internet adoption as well, thus generating more demand for firms' goods and services, and hence potentially their decision to adopt broadband. Our region-year fixed effects take into account these channels.

in either dimension i.e., region-year fixed effects (α_{st}) account for all local expansion and adoption in broadband infrastructure, along with its aggregate impact on input and output markets, while industry-year fixed effects (α_{jt}) control for sector-wide changes in demand, technology, or other sector-specific shocks. The interaction of these two channels allows us to separate the effect of broadband adoption from general economic trends in either the region or the sector.

We then estimate the following first-stage regression specification:

$$\mathbb{1}(\text{Broadband Internet})_{it} = \alpha_i + \alpha_{st} + \alpha_{jt} + \gamma Z_{ijrt} + \varepsilon_{it} \tag{9}$$

Table 1 reports the results from the first-stage. Column (1) reports the specification with only firm and year fixed effects, while Column (2), our preferred specification, includes region-year and industry-year fixed effects as well. As reported in the table, the magnitude and statistical significance of the first stage is robust across both these specifications, with an F-statistic of over 100 in both regressions. In Figure A1, we plot the relationship between residualized broadband adoption and the residualized instrument, conditional on all fixed effects, and find a tight linear relationship across the entire distribution, increasing our confidence in the identification strategy.

A last potential remaining concern with our identification strategy is that firms may select into broadband adoption based on anticipatory trends in firm performance. For example, firms expecting to grow in the future may adopt broadband in advance. While our fixed effects structure controls for rich time-varying heterogeneity at the region and industry level, along with time-invariant firm characteristics, it does not directly rule out firm-level selection on unobservables that evolve just prior to adoption.

We assess this possibility in Appendix C.3. First, we estimate a dynamic event study specifications centered around the year of broadband adoption, incorporating recent econometric advances made in this literature (Malgouyres et al., 2019; Sun and Abraham, 2021; Dube et al., 2023; De Chaisemartin and d'Haultfoeuille, 2024). We regress key measures of firm performance — fraction of workers using computers and the internet, total workers and capital expenditure, real output, costs, and value-added — on a series of year indicators relative to the year of adoption (with the year prior to adoption as the reference). The key is to examine whether outcomes trend upward (or downward) in the years before treatment. Across all these outcomes we find that the coefficients are statistically indistinguishable from zero in the pre-treatment period. Put together, these checks strengthen

Table 1: First Stage

	1(Broadband Internet)	
	(1)	(2)
Ln(Prov.)$_{rt}\times$ Int. Exposure$_{-i,jrt-1}$	0.02***	0.04***
	(0.00)	(0.00)
F Stat	107.72	247.29
Firm FE	Yes	Yes
Year FE	Yes	No
Ind x Year FE	No	Yes
Region x Year FE	No	Yes
R2	0.71	0.72
N	93098	93098
Firms	10964	10964

Notes: The outcome variable is a binary variable that takes the value 1 for all years after a firm reports first using broadband internet and 0 otherwise. Ln(Providers)$_{rt}$ is the inverse hyperbolic sine number of broadband service providers in a region r in a year t. Int. Exposure$_{rjt-1}$ is the lagged internet exposure in region r and industry j in year $t-1$. Column (1) reports the first-stage regression results with firm and year fixed effects, while Column (2) further adds 4-digit industry-year and region-year fixed effects. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

the credibility of our identification strategy by supporting the assumption of conditional exogeneity in adoption timing.

4 Impact on Firm Performance, Inputs, and Trade

We now turn to estimating the impact of broadband internet adoption on firm outcomes based on the empirical strategy described in the previous section. While we focus our interpretation on the 2SLS results in our analysis, we report results for both the OLS and 2SLS specifications for comparison. Our rich data allows us to explore a wide spectrum of firm-level measures, ranging from indicators of firm performance (output, sales, costs, etc.); detailed expenditure on factor inputs such as labor and capital; along with a range of mechanisms that capture changes in digital behavior, market expansion, and firm practices.

4.1 Impact on Firm Performance

We begin by estimating the impact of broadband internet adoption on firm-level performance. Table 2 presents results for four core outcomes: real value of production, real sales,

Table 2: Impact on Firm Performance

	pY		Sales		Costs		Value Added	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Broadband)	0.33***	3.38**	0.30***	3.50**	0.04***	0.34**	0.12***	1.52**
	(0.10)	(1.58)	(0.09)	(1.58)	(0.01)	(0.14)	(0.04)	(0.65)
Y Mean	7.46	7.46	7.31	7.31	0.56	0.56	2.98	2.98
N	86506	86506	86506	86506	86506	86506	86506	86506
No. of firms	10542	10542	10542	10542	10542	10542	10542	10542
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables are reported in thousands of real 2010 Colombian pesos and windsorized at the top and bottom 5th percentiles. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

real production costs, and real value added (measured in thousands of 2010 Colombian pesos). Odd-numbered (even-numbered) columns report the OLS (2SLS) results. The OLS estimates suggest modest gains from adoption, ranging from 4-7% across indicators. In comparison, the 2SLS estimates are much larger.

Before we proceed, we would like to provide a few important clarifications to understand the difference in the OLS and 2SLS estimates. Interpreting their magnitudes requires both economic and econometric considerations. First, these differences are neither surprising nor unique to our setting. OLS is likely biased downward due to both attenuation from measurement error as well as heterogeneous gains from adoption across firms. The 2SLS estimate reflects the local average treatment effect (LATE) for marginal adopters — firms that are induced to adopt broadband due to the instrument. These firms could therefore be better positioned to differentially benefit from adoption as well, when compared to the average firm.

Second, since we pool across pre- and post-adoption periods in our analysis, the estimated coefficients (both OLS and 2SLS) provide a cumulative difference in the average outcome variable across years after adopting broadband internet (around 6 on average in our sample). Therefore, as a first-order approximation, we can scale the estimated coefficients by $1/N_T$ to get an annualized difference in *levels* of the outcome variable i.e., $\frac{1}{N_T} \cdot \hat{\beta}/\overline{Y}_{Control}$. In that sense, adopting broadband internet causally increases key firm performance indicators annually by around 6%. Lastly, the fact that real value added increases (in Table

Table 3: Impact on Type of Workers

	Total		Managers		Prof./Tech.		Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Unconditional								
1(Broadband)	3.34***	16.99*	1.31***	0.94	0.15	-4.86**	1.89***	20.91***
	(0.71)	(9.41)	(0.30)	(3.53)	(0.17)	(2.34)	(0.48)	(6.38)
Y Mean	69.83	69.83	19.21	19.21	7.80	7.80	42.81	42.81
Panel B: Fraction of Total Workers								
1(Broadband)			0.00	-0.03	0.00	-0.02	-0.00	0.05**
			(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Y Mean			0.28	0.28	0.09	0.09	0.63	0.63
N	10964	10964	10964	10964	10964	10964	10964	10964
No. of Firms	OLS	OLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables are total workers (Columns 1-2), managers (Columns 3-4), professional and technical workers (Columns 5-6), and production workers (Columns 7-8). Panel A reports the unconditional regression, while Panel B controls for the total firm-size (L). All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

2) alongside input costs suggests that adoption enables more than cost pass-through: it reflects real productivity gains and more operational efficiency, something that we confirm in Appendix Table A1, where we consistently find a 0.20σ increase in firm TFP that is estimated using various methods in the literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009).

4.2 Impact on Labor and Capital Inputs

We next examine how firms adjust their input use following broadband adoption. Table 3 analyzes firm-level employment and occupational structure, while Table 4 presents the results for capital investments.

Impact on Labor Inputs. We now examine how broadband adoption affects the composition of firm employment (Table 3). We observe workers based on their occupation within the firm hierarchy such as: (i) managers and administrative workers; (ii) technicians and professionals; and (iii) workers involved in production. From Panel A of Table 3, adoption of broadband increases total firm size by around 17 workers (or 2.8 workers per year,

Column 2). This increase is driven by hiring more production workers (Column 8) and less professional and technical ones (Column 6). Panel B then examines whether broadband adoption changes the *composition* of employment across occupational categories, by holding firm size fixed. The results indicate a clear reallocation of labor away from non-production roles within the firm: a decline in managerial and technical workers (Columns 4 and 6) with a corresponding increase in production workers (Column 8).[6]

Contractual Arrangements. We also observe the nature of the contractual relationship of workers within a firm across three types of contracts: (i) permanent, payroll contracts; (ii) temporary contracts directly within the firm; and (iii) temporary contracts through third-party agencies. This is helpful to understand for substitution patterns across contracts within an occupation. Appendix Tables A3-A5 report the full breakdown across contractual arrangements for each occupation. For example, the expansion in production workers reported earlier is driven by hiring workers across all contracts (Table A5). Similarly, the reduction in professional workers is largely driven by those on payroll (Table A4), though there is some evidence that firms substitute domestic hiring with foreign ones (Table A6).

Impact on Capital Inputs. Turning to with capital in Table 4, broadband adoption increases real capital stock by around 10% annually (Column 2), which is driven by an increase in expenditure on computers (Column 4), machines (Column 6), and transportation equipment (Column 8).

Interpretation of Results. The above results provide two key insights on how broadband *scales* firm employment. First, firms expand production workers as opposed to managerial and professional ones. In that sense, broadband adoption (in this context) is not *skill*-biased, but *scale*-biased — consistent with a model of operational expansion (Bloom et al., 2014; Bartik et al., 2023) as opposed to complementing non-routine cognitive labor (Autor et al., 2003; Akerman et al., 2015). Second, firms also increase usage of both ICT and production capital. In Sections 5 and 6, we will show structurally how broadband adoption impacts firms through multiple channels that provide better external market access, lower frictions in access to inputs, as well as substitution patterns across them. These will help unpack the underlying drivers that drive the above (reduced-form) patterns.

[6]We see a similar pattern in wage-bill instead of firm size, as reported in Appendix Table A2.

Table 4: Impact on Capital

	Total		Comp.		Machines		Transp.		Land/Bldng	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1(Broadband)	0.14***	1.86**	0.00***	0.04***	0.09***	1.19**	0.01***	0.08***	0.03	0.52
	(0.04)	(0.73)	(0.00)	(0.01)	(0.03)	(0.47)	(0.00)	(0.03)	(0.02)	(0.39)
Y Mean	2.90	2.90	0.07	0.07	1.61	1.61	0.10	0.10	1.06	1.06
N	84169	84169	84169	84169	84169	84169	84169	84169	84169	84169
No. of firms	10381	10381	10381	10381	10381	10381	10381	10381	10381	10381
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: pace0.2cm *Notes:* The outcome variables in the above table are total capital expenditure (Columns 1-2), capital expenditure on machines (Columns 3-4), transportation equipment (Columns 5-6), and land and buildings (Columns 7-8). All outcome variables are reported in thousands of real 2010 Colombian pesos and windsorized at the the 95th percentile. All regressions include firm, region-year and 4-digit industry-year fixed effects. $1(\text{Broadband})_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Table 5: Impact on Cost Shares

	Admin. Workers		Prod. Workers		Computer Exptd.		Prod. Capital	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Broadband)	0.01***	0.03	0.01*	0.20***	0.00***	0.03*	-0.02***	-0.25***
	(0.00)	(0.03)	(0.00)	(0.06)	(0.00)	(0.01)	(0.00)	(0.08)
Y Mean	0.20	0.20	0.39	0.39	0.07	0.07	1.63	1.63
N	84136	84136	84136	84136	84136	84136	84136	84136
No. of firms	10388	10388	10388	10388	10388	10388	10388	10388
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables in Columns (1)-(6) are binary variables that take the value 1 if a firm reports any international trade (Columns 1-2), exports (Columns 3-4), and imports (Columns 5-6). Columns (7)-(8) report the share of exports in total sales, while Columns (9)-(10) report the share of imports in total cost or raw materials. All regressions include firm, region-year and 4-digit industry-year fixed effects. $1(\text{Broadband})_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

4.3 Impact on International Trade

We now examine whether broadband adoption facilitates firms' participation in international markets. Access to high-speed internet may reduce information frictions, enable faster and more reliable communication with international buyers and suppliers, and allow firms to coordinate production, logistics, and payments across borders.

Table 6: Impact on International Trade

	1(Trader)		1(Exporter)		1(Importer)		X Share		M Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1(Broadband)	0.01***	0.09	0.01**	0.12**	0.01	0.06	0.01**	0.11**	0.00	0.00
	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)	(0.05)	(0.00)	(0.06)	(0.00)	(0.03)
Y Mean	0.34	0.34	0.27	0.27	0.21	0.21	0.27	0.27	0.07	0.07
N	93089	93089	93089	93089	93089	93089	93089	93089	93089	93089
No. of firms	10963	10963	10963	10963	10963	10963	10963	10963	10963	10963
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables in Columns (1)-(6) are binary variables that take the value 1 if a firm reports any international trade (Columns 1-2), exports (Columns 3-4), and imports (Columns 5-6). Columns (7)-(8) report the share of exports in total sales, while Columns (9)-(10) report the share of imports in total cost or raw materials. All regressions include firm, region-year and 4-digit industry-year fixed effects. $1(\text{Broadband})_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Table 6 reports the results on both the extensive and intensive margins of trade. The extensive margin is captured by binary indicators for whether a firm engages in any international trade, exports, or imports (Columns 1-6). The intensive margin is measured by the share of exports in total sales and the share of imports in total costs (Columns 7-10).[7] Broadband adoption increases the probability of having any international trade by around 10 p.p. (Column 2). This is driven primarily a 12 p.p. increase in the probability of exporting and an 11 p.p. increase in exports as a share of sales (Columns 4 and 8). In contrast, there is little change in import behavior (Columns 6 and 10). Both the magnitudes (as compared to exports) are small and statistically insignificant at conventional values.

As we will discuss below, this asymmetric impact is potentially consistent with broadband lowering fixed costs of demand-side market access, where broadband adoption increases the likelihood that firms participate in e-commerce, use websites to engage customers, and send or receive online orders.

4.4 How Do Firms Use Broadband Internet?

Preceding sections show that broadband adoption improves firm performance, trade, and alters the composition of key inputs. However, *how* these gains materialize operationally within the firm remains an open question. A novel contribution of our paper is to be able

[7] We set the share of exports and imports to zero for firms that are non-exporters and non-importers respectively.

Table 7: Impact on Computer Usage and Expenditure

	Frac. Computer Use		Frac. Internet for Work	
	(1)	(2)	(3)	(4)
1(Broadband)	0.02***	0.06*	0.02***	0.06
	(0.00)	(0.04)	(0.00)	(0.04)
Y Mean	0.38	0.38	0.36	0.36
N	85299	85299	85299	85299
No. of firms	10869	10869	10869	10869
Regression	OLS	2SLS	OLS	2SLS

Notes: The outcome variable is the fraction of workers in a firm that use computers (Columns 1-2) and the internet for their work (Columns 3-4) respectively. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable for firms. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

to exactly unpack these changes. We examine a range of complementary outcomes that trace how firms take advantage of digital technologies for external market access (online sales, e-commerce, etc.), as well as internal changes driven by production operations and organizational practices.

As reported earlier in Table 4, firms increase expenditure on computers. Table 7 shows a 6 p.p. (15%) increase in the fraction of workers who use a computer (Column 2) or use the internet for work-related activities (Column 4). Table 8 examines *how* firms use the internet and reports the effects of broadband adoption on a wide range of digital practices. Each outcome variable is a binary variable that takes the value 1 after a firm first reports using the internet for the activity of interest, and 0 otherwise. Consistent with the structure of the theory (Section 2), we categorize these activities in those that improve firms' market access (Panel A) and those that improve production efficiency within a firm (Panel B).

External Market and Customer Access. From Panel A, adopting broadband increases the probability of having a firm website by 17 p.p. (Column 2), providing online customer service by 12 p.p. (Column 4), sending or receiving online orders by 18 p.p. (Column 6), and participating in e-commerce related activities by 17 p.p. (Column 8). These suggest that broadband enables firms to adopt digital interfaces for customer engagement, market access, and online transactions, thus reinforcing prior evidence (Section 4.3) on expanded participation in international trade.

Table 8: Usage of Internet for Information and Online Firm Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: External Market Activities (N = 85779; Firms = 10882)								
	Website		Customer Service		Send/Receive Orders		e-Commerce	
1(Broadband)	0.03***	0.17***	0.03***	0.12**	0.02***	0.18***	0.02***	0.17**
	(0.00)	(0.06)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)	(0.08)
Y Mean	0.71	0.71	0.86	0.86	0.85	0.85	0.55	0.55
Panel B: Internal Firm Activities (N = 58362; Firms = 9736)								
	Hiring		Training		Use Apps		Use VoIP	
1(Broadband)	0.06***	0.28***	0.07***	0.23***	0.09***	0.27***	0.07***	0.31***
	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.08)
Y Mean	0.46	0.46	0.59	0.59	0.76	0.76	0.57	0.57

Notes: All outcome variables in the above table are binary variables that take the value 1 for all years after a firm first reports using the internet for that activity, and 0 otherwise. In Panel A, the outcome variables are whether a firm has: (i) a website (Columns 1-2); (ii) provides online customer support (Columns 3-4); (iii) sends or receives online orders (Columns 5-6); (iv) participates in e-commerce (Columns 7-8). In Panel B, the outcome variables are whether a firm uses the internet for: (i) hiring and training workers (Columns 1-4); (ii) uses applications that need the internet (Columns 5-6); (iii) uses VoIP phone or video facilities (Columns 7-8). The sample size is smaller for e-Commerce and all variables in Panel B since they were only included in surveys from 2012 onwards. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable for firms not using broadband internet. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Internal Firm Operations. Panel B then examines the impact on internal firm practices. Broadband adoption substantially increases the likelihood of online worker hiring and training by around 25 p.p. (Columns 2 and 4), usage of internet applications and workflow VoIP tools (like video conferencing facilities, for example) by around 30 p.p. (Columns 6 and 8). These patterns help rationalize how firms expand their scale without proportional increases in professional and managerial workers (see Section 4.2).

Discussion. Taken together, these results show that broadband adoption induces widespread digitization of firm practices, both externally (through websites, customer engagement, and e-commerce) and internally (through hiring and communication). They align with the model from Section 2, which posits that broadband acts through multiple channels that improve market access as well as frictions in accessing key inputs (notably, labor). Yet they do not reveal *which* channels are quantitatively important. This highlights the need to structurally estimate the theoretical model to decompose the observed firm-level and aggregate outcomes into underlying changes in key barriers and frictions. We explore

this decomposition in Sections 5 and 6 below.

5 A Quantifiable Model of Broadband Adoption

Section 2 provides a general framework through which broadband adoption can impact firm production in multiple ways. Our empirical results in Section 4 document these channels in a reduced-form way. However, it is limited in assessing the quantitative importance of these channels, which we now turn to in Sections 5 and 6.

Note that quantifying these changes requires a framework where firms can expand scale, substitute flexibly across inputs, and face adoption-induced changes in both demand and input choices. Standard production structures are not well-suited for this purpose. For example, a standard Cobb–Douglas production function imposes fixed cost shares and hence cannot generate flexible substitution patterns. A constant-elasticity-of-substitution (CES) technology allows for substitution but restricts the elasticity to be identical across all input pairs, which is inconsistent with the heterogeneous firm responses across different types of labor and capital inputs. We therefore adopt a variable elasticity of substitution (VES) production function that permits input-specific substitution and complementarity patterns while remaining tractable in aggregation.

5.1 A Model of Firm Production

Consumer Preferences. An economy consists of two sectors: manufacturing (m) and non-manufacturing (n). A representative household as Cobb-Douglas preferences across sectors given by $U = \prod_{s=\{m,n\}} C_s^{\beta_s}$, with $\sum_s \beta_s = 1$. These imply sectoral expenditures given. by $P_s C_s = \beta_s I$. Within manufacturing, firms produce a a continuum of differentiated varieties $f \in \Omega$ aggregated by CES with elasticity $\sigma > 0$:

$$C_m = \left(\int_{f \in \Omega} \lambda_{x,f}^{\frac{1}{1+\sigma}} y_f^{\frac{\sigma}{1+\sigma}} \, \mathrm{d}f \right)^{\frac{1+\sigma}{\sigma}}, \qquad P_m = \left(\int_{f \in \Omega} \lambda_{x,f} p_f^{-\sigma} \, \mathrm{d}f \right)^{-\frac{1}{\sigma}}, \tag{10}$$

where: λ_x captures a firm's "market access" defined below. Each firm f then faces a demand curve:

$$p_f y_f = \lambda_{x,f} \left(\frac{p_f}{P_m} \right)^{-\sigma} P_m C_m. \tag{11}$$

Market Access (λ_x). A key object of interest is λ_x, which scales the level of demand faced by a firm. It can offer several interpretations related to a measure of consumers who can access firm (extensive margin), or the probability that firm is successfully matched with a

consumer in an environment with search and matching frictions, or the fraction of potential transactions that convert into effective delivered demand net of informational, coordination, or transaction costs. Under any of these microfoundations, broadband adoption increases λ_x by enabling firms to advertise online, receive orders digitally, interact with customers remotely, and access export markets.

Production Function. Each firm is indexed by a (Hicks-neutral) productivity $z \sim F(z)$ and uses N variable inputs in production, given by $\boldsymbol{\ell} = (l_1, \ldots, l_N)^\top$. Corresponding factor prices and input frictions are given by $\boldsymbol{w} = (w_1, \ldots, w_N)^\top$ and $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_N)^T$ respectively. In other words, input prices (w_i are augmented by input-specific frictions (λ_i that capture hiring, monitoring, contracting, or utilization costs. Broadband adoption can reduce these frictions differentially across inputs, thereby changing effective factor prices faced by the firm, given by: $\widetilde{w}_i = \lambda_i w_i$.

We parameterize the production function using a variable elasticity of substitution (VES) function. It allows the marginal productivity (and cost shares) of any input to depend on the usage of other inputs, generating flexible substitution and complementarity patterns.

Let a firm of productivity z produce an output y given by: $y = q(z, \boldsymbol{\ell}) = zq^{\frac{1}{\phi}}$, where:

$$q = \sum_{i=1}^{N} q_i = \sum_{i=1}^{N} \left[a_i \, l_i^{\phi} \; + \; \frac{1}{2} \sum_{j=1}^{N} b_{ij} \left(l_i l_j \right)^{\frac{\phi}{2}} \right] \tag{12}$$

As we will show later, q_i/q gives the cost-share of input i, which is helpful in interpreting the role of a_i and b_{ij}. For an input i, a_i captures cost shares (similar to Cobb-Douglas) in the absence of any substitution patterns (b_{ij}). b_{ij} then govern how the usage of one input i responds to the usage of another input j. Positive values of b_{ij} imply complementarity between inputs i and j, while negative values imply substitutability.

Broadband adoption operates through *multiple* channels that alter effective input prices and scale. The VES structure therefore allows for flexible shifts in cost shares through these parameters, providing a disciplined, data-driven mapping between input use and production.

Firm Production Choices. Firms choose their input mix to maximize (variable) profits:

$$\pi(l; z) = py \; - \sum_i \widetilde{w}_i l_i \;\; \text{s.t.} \;\; py = \lambda_x^{\frac{1}{1+\sigma}} \left(\frac{y}{C_m} \right)^{\frac{\sigma}{1+\sigma}} P_m C_m; \quad y = zq^{\frac{1}{\phi}}.$$

Lemma 1. *Define $c_q = \min_{l_i} \sum_i \widetilde{w}_i l_i : q(l_i) = 1$ as the unit cost of production so that the cost of producing one unit y will be given by c_q/z. Let $\kappa_i = q_i/q$ be the cost share of input i. Then prices (p), revenues (x), input expenditure ($\widetilde{w}_i l_i$), and variable profits (π) are given by:*

$$\widetilde{w}_i l_i = \frac{\sigma}{1+\sigma} \cdot \kappa_i x \qquad \textit{(Expenditure on Input i)} \tag{13}$$

$$p(z) = \frac{1+\sigma}{\sigma} \cdot \frac{c_q}{z} \qquad \textit{(Prices)} \tag{14}$$

$$x = \psi_x z^{\sigma} \qquad \textit{(Revenues)} \tag{15}$$

$$\pi(z) = \frac{\psi_x z^{\sigma}}{1+\sigma} \qquad \textit{(Profits)} \tag{16}$$

where $\psi_x = \left(\frac{1+\sigma}{\sigma}\frac{c_q}{P_m}\right)^{-\sigma} \lambda_x P_m C_m$.

Appendix B.3 provides the proof. Monopolistic market structures give standard results where firms charge a constant markup over marginal cost, revenues scale with productivity, and total variable costs are a fixed fraction of revenues. Expenditure on each input is proportional to firm revenues, with cost shares determined endogenously by the production technology and effective input prices.

5.2 Broadband Adoption, Aggregate Input Demand, and Sales

We now characterize how broadband adoption affects firm behavior and aggregate outcomes in equilibrium. But before we do, consider the following definitions. First, for any variable of interest v, $v^{(b)}$ denotes the status of adoption, where $b \in \{0,1\}$. Second, V denotes the aggregate value of the variable across all firms in the economy (e.g. total sales, etc.) and $\overline{V}$ denotes the value of the representative firm (i.e., average value across all firms).

Fraction of Adopters. Firms incur a fixed cost to enter (F_e) and adopt broadband (F_b). As a result, entry and adoption are profitable only for firms above productivity thresholds z_e and z_b respectively. These thresholds jointly pin down the fraction of adopters in the economy and the composition of production across adopting and non-adopting firms. Assume that firm productivity follows a Pareto distribution given by: $F(z) = 1 - z^{-\theta}$. Define $\widetilde{\theta} = \sigma/\theta < 1$. Then the fraction of *incumbent* firms that adopt broadband can be given by: $\xi(z_e) \equiv \frac{1-F(z_b)}{1-F(z_e)} = (z_e/z_b)^{\theta}$.

Aggregate TFP, Sales, and Input Demand. From Equation (15), note that $x^{(b)}(z) = \psi_x^{(b)} \cdot z^\sigma$ and $\widetilde{w}_i l_i = \frac{\sigma}{1+\sigma}\kappa_i^{(b)} x^{(b)}$. Total and average TFP and sales, and demand for input i in the economy will be a weighted average across these firms, given by Lemma 2 below.

Lemma 2. *Total and average TFP and sales, and total demand for input i can be given by:*

$$Z = (1-\widetilde{\theta})^{-1} \; z_e^{\sigma-\theta} \qquad \textit{and} \quad \overline{Z} \equiv [E(z^\sigma | z \geq z_e)]^{\frac{1}{\sigma}} = (1-\widetilde{\theta})^{-\frac{1}{\sigma}} z_e \tag{17}$$

$$X = \Psi_x Z \qquad \textit{and} \quad \overline{X} \equiv E(X | z \geq z_e) = \Psi_x \overline{Z}^\sigma \tag{18}$$

$$L_i = \left(\frac{\sigma}{1+\sigma}\right) \frac{\Psi_i Z}{w_i} \tag{19}$$

where $\Psi_x = (1-\xi^{1-\widetilde{\theta}})\psi_x^{(0)} + \xi^{1-\widetilde{\theta}}\psi_x^{(1)}$; *and* $\Psi_i = (1-\xi^{1-\widetilde{\theta}}) \; \frac{\kappa_i^{(0)}\psi_x^{(0)}}{\lambda_i^{(0)}} + \xi^{1-\widetilde{\theta}} \; \frac{\kappa_i^{(1)}\psi_x^{(1)}}{\lambda_i^{(1)}}$.

See Appendix B.4 for proof. Lemma 2 suggests that broadband adoption affects aggregate sales through two channels. First, adopters generate higher revenues conditional on productivity (Ψ_x) because of improved market access and lower effective marginal costs. Second, changes in the adoption threshold alters the composition of firms who adopt broadband. These composition effects amplify the direct firm-level gains from adoption and are quantitatively important for aggregate outcomes. Broadband adoption increases input demand not only through scale (ψ_x), but also through two additional channels: lower input frictions λ_i, and changes in input intensities through endogenous cost shares.

Productivity Thresholds for Entry and Adoption. Let $\{F_e, F_b\}$ denote fixed costs of entry and adoption. The corresponding threshold productivities $\{z_e, z_b\}$ can be given by:

$$z_b^\sigma = \frac{(1+\sigma)F_b}{\psi_x^{(1)} - \psi_x^{(0)}} \quad \textit{and} \quad z_e^\sigma = \frac{(1-\widetilde{\theta})(1+\sigma)(F_e + \xi F_b)}{\Psi_x} \tag{20}$$

See Appendix B.5 for the proof.

5.3 Aggregate Income and Equilibrium Prices

We now characterize equilibrium prices, aggregate income, and factor prices. Broadband adoption affects aggregate outcomes not only through firm-level expansions and reallocation, but also through adjustments in goods and factor prices, and income in equilibrium.

Manufacturing Price Index. The manufacturing price index (P_m) can be given by:

$$P_m = \left(\frac{1+\sigma}{\sigma}\right) \cdot \frac{C_q}{\overline{Z}} \tag{21}$$
$$where: C_q = \left[(1-\xi^{1-\widetilde{\theta}})\lambda_x^{(0)}(c_q^{(0)})^{-\sigma} + \xi^{1-\widetilde{\theta}}\lambda_x^{(1)}(c_q^{(1)})^{-\sigma}\right]^{-\frac{1}{\sigma}}$$

See Appendix B.6 for the proof. P_m aggregates prices charged by all active firms, accounting for heterogeneity in productivity and adoption status. It therefore depends on the distribution of unit production costs across adopters and non-adopters, weighted by their market access.

Aggregate Income. The total income generated in the economy is equal to factor payments in both the manufacturing and non-manufacturing sector, profits earned by manufacturing firms, and resource wedges that are rebated back to consumers, i.e., $I = I_n + I_m$.[8] Aggregate income therefore captures both direct gains from higher productivity and indirect gains from price reductions.

Input Prices. We assume a representative firm in the non-manufacturing sector that uses inputs L_{Ni} to produce output, given by: $Y_N = A_N \prod_i L_{Ni}^{\alpha_i}$, where $\sum_i \alpha_i = 1$. This implies that equilibrium factor prices are pinned down by:

$$w_i = \alpha_i \frac{(1-\beta_m)I}{1-L_i} \tag{22}$$

where L_i is the aggregate demand for input i in the manufacturing sector (Equation 19), and we normalize the aggregate stock of each input to equal 1. Broadband adoption raises demand for inputs used intensively by adopting firms, thus increasing their price as well. This partially offsets the direct cost reductions associated with adoption.

Equilibrium. An equilibrium in this economy consists of productivity thresholds for entry and broadband adoption, a set of factor and goods prices in both sectors, and an allocation of inputs across sectors, such that: (i) the productivity thresholds for firm entry and broadband adoption $\{z_e, z_b\}$ are determined by Equations (20); (ii) firms maximize profits; and (iii) factor and goods markets clear.

[8] Rebating the wedges back to consumers ensures that changes in counterfactuals are not mechanically driven by lower deadweight losses in the economy, but reflect meaningful real changes.

6 Decomposing the Impact of Broadband Adoption

We now estimate the model parameters using firm-level data, followed by using them to conduct counterfactual analyses to decompose the contribution of different broadband channels to aggregate output and welfare.

6.1 Parameter Estimates

We begin by discussing the calibration of the model. All parameters in the model can be classified into three categories, namely: (a) fundamental parameters related to consumer demand and the productivity distribution $\mathcal{D} = \{\sigma, \beta_m, \theta, \{\alpha_i\}_{\forall i}\}$; (b) parameters of the production function $\mathcal{P} = \{\phi, \{a_i\}_{\forall i}, \{b_{ij}\}_{\forall i,j}\}$ and fixed costs of entry and adoption $\mathcal{F} = \{F_e, F_b\}$; and (c) parameters that change with the adoption of broadband, $\mathcal{L} = \{\lambda_x, \{\lambda_i\}_{\forall i}\}$.

We use the demand-side parameters from the literature. We set the consumer expenditure share on manufacturing (β_m) equal to 0.3, using the average manufacturing share in GDP in Colombia between 2008-2019 from the World Bank database. We set $\sigma_d = 1.2$ following the median value in Broda and Weinstein (2006).

Productivity Distribution. Following the literature, we estimate θ using the top 1% of (residualized) sales from the EAM data. We con sider three measures of sales (X), namely: (i) real sales; (ii) real value of production pY; and (iii) model-implied sales that are equal to $\frac{1+\sigma}{\sigma} \times$Total Costs (from Equation 13). To isolate persistent productivity differences, we residualize firm-level sales ($\widehat{X}$) using region-year and four-digit industry-year fixed effects. We then estimate θ using either $\widehat{X}$ directly, or the firm fixed effect from $\widehat{X}$. The results are reported in Table 9 and range between 3-3.88 across different specifications. For our baseline model, we therefore set $\theta = 3.25$, which is the average across these values.

Production Function. We now turn to estimating the parameters of the VES production function in $\mathcal{P}$. We impose three normalizations. First, cross-input interactions are symmetric i.e., $b_{ij} = b_{ji}$. Second, from Equation (12), the own- and cross-inputs parameters are only identified up to a scale parameter.[9] Therefore, without loss of generality, we set $\sum_i a_i = 1$. Lastly, the own-quantity effect is given by: $(a_i + b_{ii}) l_i^{\phi}$. Therefore, again without loss of generality, we set $b_{ii} = 0$ and identify a_i from the data.

[9]For example, if we scale all parameters a_i and b_{ij} by a factor A (say), then all q_i will scale by A leaving the cost-shares (κ_i) unchanged.

Table 9: Parameter Estimates of θ

	Real Sales	Real pY	$\left(\frac{1+\sigma}{\sigma}\right)$ Total Costs
	(1)	(2)	(3)
Residualized X	3.00	3.07	3.27
Firm F.E.	3.20	3.03	3.88

Notes: The above table reports estimates of θ from the EAM data between 2008-19. Each column shows the underlying variable X used for the estimation, which is real sales (Column 1), real value of production (Column 2), model-based sales from Equation (13). We first residualize X using region-year and 4-digit industry-year fixed effects. The first row then reports the estimates from the top 1% of residualized X. The second row reports the estimates from a firm fixed effect the residualized X.

Table 10: Parameter Estimates of the Production Function

	L_a	L_p	K_a	K_p
	(1)	(2)	(3)	(4)
Panel A. Estimates of a_i				
	0.21	0.32	0.01	0.47
	(0.004)	(0.004)	(0.003)	(0.004)
Panel B. Estimates of b_{ij}				
L_p	-0.06			
	(0.010)			
K_a	0.04	-0.01		
	(0.004)	0.004		
K_p	-0.16	-0.25	0.01	
	(0.013)	0.017	0.005	

Notes: The above table reports estimates of θ from the EAM data between 2008-19. Each column shows the underlying variable X used for the estimation, which is real sales (Column 1), real value of production (Column 2), model-based sales from Equation (13). We first residualize X using region-year and 4-digit industry-year fixed effects. The first row then reports the estimates from the top 1% of residualized X. The second row reports the estimates from a firm fixed effect the residualized X.

With the above assumptions, we estimate the production parameters as follows: first, we residualize (log) input quantities with region-year and four-digit industry-year fixed effects. For a vector of parameters $\mathcal{P}$, we construct the model-implied cost-shares $\widehat{\kappa}_i$ for each firm-year using their inputs (l_i). We then estimate $\widehat{\mathcal{P}}$ using non-linear least squares.

We estimate $\widehat{\phi} = 0.46$ $[se = 0.031]$, which implies an elasticity of substitution (in a CES framework) of 1.84. Table 10 reports the estimates for a_i and b_{ij} across inputs. Panel A reports the estimates of a_i, which can be interpreted as local cost shares (analogous to

Cobb–Douglas shares) but after accounting for flexible substitution patterns across inputs. The estimates indicate that the overall share of labor inputs is around 0.53, with a 0.21 and 0.32 share of administrative and production labor respectively (Columns 1-2). The share of production capital is around 0.47 (Column 4), with a negligible share of administrative capital (K_a). All estimates are precisely estimated and in line with capital and labor shares in manufacturing across various contexts.

Panel B reports the estimates for b_{ij}, which govern the substitutability across inputs. Two patterns stand out. First, ICT capital (K_a) exhibits a complementarity with administrative labor (L_a), consistent with the empirical evidence that digital tools enhance coordination, communication, and managerial oversight.

In contrast, productive capital (K_p) is substitutable with labor. For production workers, this reflects standard channels of mechanization and automation in manufacturing, where machines replace workers in production tasks. The lower (but still negative) interaction with administrative labor suggests that productive capital also reduces some demand for administrative workers. A small complementarity between K_p and K_a indicates that production capital is more effective when supported by ICT infrastructure.

Input Frictions. We now turn to estimating the input frictions parameters in $\mathcal{L}$. For each firm-year, we construct effective input prices using observed quantities and expenditures: average wages for administrative and production workers, user costs for ICT capital based on expenditures and quantities of computers, and user costs for production capital based on deflated machinery investment (available from the Bank of Colombia).

We then take the implied log price for input i in firm f and year t as a proxy for $\ln \widetilde{w}_{ift}$. Through the lens of our model, $\ln \widehat{w}_i = \ln w_i + \ln \lambda_i$. We therefore estimate the 2SLS regression in Equation (8), which allows us to isolate changes in frictions associated with broadband adoption. We normalize frictions for non-adopters to one.

Columns (1)-(4) of Table 11 report the estimates for the four inputs. In particular, we see that broadband adoption significantly reduces the input costs for production workers (13%), with little impact on other inputs. This is consistent with the empirical results previous sections that show how firms expanded by hiring more production workers.

Market Access. We identify market access, λ_x, using the structure of the firm's revenue function. From Lemma 1, net of aggregate changes, firm-level sales growth can be decomposed into changes in market access (λ_x) and changes in unit production costs (c_q).

Table 11: Parameter Estimates of Market Access and Input Price Frictions

λ_{La}	λ_{Lp}	λ_{Ka}	λ_{Kp}	λ_{x}
(1)	(2)	(3)	(4)	(5)
1.01***	0.87***	0.98***	1.00***	1.13***
(0.09)	(0.05)	(0.19)	(0.00)	(0.19)

Notes: The above table reports estimates of input price frictions (Columns 1-4) and market access (Column 5). using the EAM data between 2008-19. L_a and L_p are administrative and production workers respectively. K_a and K_p are ICT and production capital respectively. λ_x is a parameter for market access. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Since unit costs are not directly observed, we construct them using estimated production parameters and firm-level input data.[10] Regressing log real sales on a binary variable of broadband adoption using 2SLS (Equation 8) and controlling for $\ln c_q$ yields $\lambda_x = 1.13$ (Column 5, Table 11). This implies that adopting market access improves market access by 13%. This is consistent with the observed expansion in exports, online transactions, and customer-facing digital activities documented in Section 4, and confirms that broadband relaxes demand-side constraints in addition to altering firm production.

Other Parameters. The remaining parameters pertain to the input shares in the non-manufacturing sector (α_i) and the fixed cost of entry and adoption. For each year, we simulate the model in equilibrium and calibrate the α_i to match the average cost-share in input i. The fixed cost of adoption (F_b) are calibrated to match the adoption rate. To calibrate the entry costs, we need to know the mass of potential entrants, which we assume to be 1.5 times the total number of firms observed in the EAM. We then calibrate the fixed cost of entry (F_e) to equal the fraction of firms that are active.

Lastly, we take the aggregate price index in the economy $P = \prod_{j=\{m.n\}}(P_j/\beta_j)^{\beta_j}$ as the numeraire. Aggregate capital stocks are normalized to be equal 1. For labor, we treat administrative and production workers as separate labor markets. We adjust their stock to equal the ratio of skilled workers (those with a high-school degree) to unskilled workers in Colombia.

[10] For each firm-year, we use input quantities (l_i) and estimates of the production function parameters ($\mathcal{P}$) to construct a firm-(year) level q. c_q is then simply empirical total costs per unit q.

Table 12: Aggregate Impacts on Manufacturing Output and Real Income

	Y_m	Real I
	(1)	(2)
Fix λ_K	0.00	0.00
Fix λ_L	-4.64	-0.82
Fix λ_X	-6.54	-1.27
Fix all λ	-6.99	-1.35

Notes: Each row of the above table shows the percentage change in Y_m (Column 1) and real income (Column 2) relative to the status quo when we fix a λ parameter to 1.

6.2 Aggregate Impact and Drivers of Broadband Adoption

With the parameter estimates in hand, we now use the model to assess the aggregate impact of broadband as well as the channels that drive it. A key advantage of the structural framework is that it allows us to isolate individual channels — market access, input frictions, and equilibrium price adjustments — while preserving interactions among firms, factor markets, and consumers in equilibrium.

Aggregate Impact. We begin by examining the aggregate impact of broadband adoption through a series of counterfactual simulations. In each counterfactual, we selectively eliminate one channel through which broadband affects firms by fixing the corresponding parameter — either market access (λ_x), input frictions (λ_i), or both — to its non-adoption value (equal to 1), while allowing other parameters and equilibrium prices to adjust endogenously. We then examine the percentage change in manufacturing output (Y_m) and real income (our measure of welfare) relative to the status quo baseline.

The results are reported in Table 12. Eliminating broadband-induced changes in capital-related frictions i.e., setting $\lambda_K = \{\lambda_{Ka}, \lambda_{Kp}\} = 1$, has virtually no effect on aggregate output or real income. This reflects the fact that capital-related input frictions are quantitatively small anyway (from Table 11). In other words, while firms increase capital usage after adoption, this occurs primarily through scale expansion and complementarities rather than through a direct reduction in the effective cost of capital.

In contrast, eliminating reductions in labor-related frictions has large aggregate effects — reducing manufacturing output and real income by 4.6% and 0.8% respectively. These effects are driven almost entirely by frictions associated with production labor (see Table 11) and mirror the reduced-form evidence in Section 4 as well, where broadband adop-

tion disproportionately expands employment in frontline production roles rather than managerial or professional occupations. In the model, lower hiring and adjustment costs for production workers allow firms to scale output more efficiently, and shutting down this channel substantially attenuates aggregate gains.

Eliminating improvements in market access has similarly large effects. When λ_x is fixed at its non-adoption value, manufacturing output falls by 6.5% and real income by 1.2% relative to the baseline. These losses reflect the importance of demand-side expansion in scaling firm revenues and reallocating activity toward more productive firms. Finally, shutting down all broadband-related advantages reduces manufacturing output by approximately 7% and real income by 1.35%.

Decomposing Firm-Level Channels of Output Growth. The theoretical model in Section 2 shows that firm-level output growth following broadband adoption is driven by three components: changes in market access, changes in real unit production costs, and changes in aggregate demand. We now examine the relative importance of these channels in firm expansion.

For a variable $\ln v$, denote $\ln v'$ to be the change in $\ln v$ due to the adoption of broadband. From Lemma 1, we can express Proposition 1 as follows:

$$\underbrace{\ln y'}_{\triangle\text{Output}} = \underbrace{\ln \lambda_x'}_{\triangle\text{Market access}} - \underbrace{\sigma \ln(c_q/P_m)'}_{\triangle\text{Real unit cost of prod.}} + \underbrace{\ln C_m'}_{\triangle\text{Agg. demand}} \tag{23}$$

We quantify the contribution from these channels by comparing the change in each variable from a baseline scenario where there is no broadband at all, to one with endogenous broadband adoption. As reported in the first row of Table 13, market access explains around 40% of the expansion in firm output. Lower unit costs explain 36%, and the rest (24%) are explained through aggregate changes in equilibrium. This decomposition highlights that firm expansion following broadband adoption is not driven solely by one channel alone. Demand-side and cost-side improvements are both quantitatively important, followed by equilibrium changes in aggregate prices. This underscores the importance of modeling broadband as a multi-dimensional shock.

A key insight from Proposition 2 was to demonstrate that while broadband adoption can help firms expand, *how* they do it operates through four distinct channels: (i) changes in input frictions (λ_i); (ii) a scale effect due to higher output; (iii) substitution effects across

Table 13: Decomposing the Drivers of Firm Expansion

Channel:	λ	c_q	Scale	κ_i	G.E.
	(1)	(2)	(3)	(4)	(5)
y	0.40	0.36			0.24
L_a	-0.10		2.06	-0.55	-0.41
L_p	0.24		0.50	0.46	-0.20
K_a	0.12		1.93	-0.64	-0.41
K_p	-0.08		8.56	-5.80	-1.67

Notes: The above table reports the contribution of various channels to firm expansion. The first row decomposes changes in (log)output, followed by changes in log inputs L_p, L_a, and K_p respectively. Each column reports the contribution of a channel.

inputs driven by production (κ_i); and (iv) equilibrium changes in real input prices.

Table 13 reports the relative contribution of each channel across inputs. A key feature of this decomposition is that while the contribution across all channels sum to one, any individual component may exceed one or be negative. A contribution greater than one indicates that, in isolation, a given channel would increase input usage by more than the net observed change, but its effect is partially offset by other channels. Negative contributions indicate channels that act to counteract expansion driven by other forces.

Consider production labor. The dominant forces driving its expansion are scale effects and reductions in hiring frictions. On its own, the reduction in λ_{L_p} contributes to roughly a 25 percent increase in output and a large increase in labor demand. However, as production labor expands, wages rise in equilibrium. This wage response appears in the general-equilibrium component (Column 5), which offsets approximately 20 percent of the partial-equilibrium expansion. Despite this offset, the scale effect remains large enough that net production employment increases substantially.

For other inputs, large positive scale effects are offset by substitution away from these inputs and rising input prices in equilibrium. As a result, while the net change is positive, these underlying forces push in opposite directions, reflecting this tension between expansion and reallocation. For example, consider administrative labor. Scale effects tend to increase demand, but substitution away from administrative tasks, enabled by ICT capital and digital coordination, offset much of this expansion. This mechanism aligns closely with the empirical evidence of managerial delayering and stable or declining non-production employment documented in Section 4.

Discussion. Taken together, these counterfactuals illustrate how broadband adoption reshapes firm behavior through interacting channels in equilibrium. A central contribution of our structural framework is to show that the empirical patterns (Section 4) cannot be explained through a single mechanism. Broadband adoption simultaneously affects demand-side access, internal hiring and contracting frictions, and reallocation of input usage within the firm. Market access primarily scales revenues and reallocates production toward more productive firms, while lower hiring frictions shape how firms expand internally. At the same time, equilibrium adjustments, particularly rising wages, partially offset these gains, underscoring the importance of accounting for price responses when evaluating the impact of technology adoption. Put together, our structural framework helps unpack the aggregate and firm-level drivers of growth.

7 Conclusion

This paper examines how the diffusion of broadband internet transformed Colombian manufacturing firms. Using rich panel data spanning over a decade, we document that adoption reshaped production, organization, and management practices along multiple margins: firms expanded sales and exports, hired more frontline production workers, primarily on contracts, and increased investments in capital, internal communication, and transportation. Embedding these patterns in a general equilibrium model of heterogeneous firms show that broadband adoption raises manufacturing output by approximately 7 percent and real income by about 1.35 percent.

More broadly, our results demonstrate that broadband internet operates as a "general-purpose technology", whose economic impact depends on the joint evolution of multiple frictions. Its importance lies not only in expanding market access, but also in enabling firms to reorganize production, adjust labor more flexibly, and substitute across inputs in response to new coordination technologies. Without a structural framework capable of capturing these interactions, it would be difficult to reconcile the observed reallocation of labor, the expansion of exports, and the aggregate welfare gains documented in the data.

Lastly, from a policy perspective, the findings suggest that the benefits of digital infrastructure depend critically on complementary conditions within firms and labor markets. Investments in broadband connectivity are likely to generate larger and more persistent gains when accompanied by institutions and practices that facilitate hiring, contracting, and the effective use of ICT. More broadly, the framework developed in this paper provides a template for analyzing the economic consequences of emerging digital technolo-

gies such as cloud computing or artificial intelligence, whose productivity effects similarly arise from the relaxation of multiple, interrelated organizational constraints rather than from a single margin alone.

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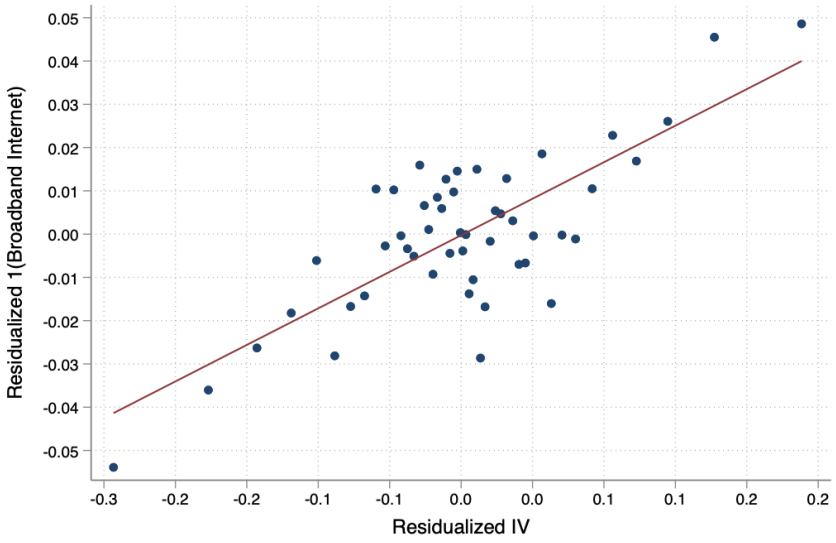
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A Tables and Figures

Figure A1: First Stage Relationship



Notes: The above figure plots the relationship between the residualized instrument (on the horizontal axis) and residualized adoption of broadband variable, $\mathbb{1}(\text{Broadband Internet})_{it}$ after accounting for firm, industry-year, and region-year fixed effects.

Table A1: Impact on TFP

	Levinsohn-Petrin		Olley Pakes		Wooldridge		Average	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Broadband)	0.00	0.21**	0.00	0.21**	0.00	0.20**	0.00	0.21**
	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.08)	(0.01)	(0.09)
Y Mean	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02	-0.03	-0.03
N	92176	92176	92176	92176	92176	92176	92176	92176
No. of firms	10888	10888	10888	10888	10888	10888	10888	10888
Regression	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The above table estimates TFP using a production function estimation approach by Levinsohn and Petrin (2003) (Column 1-2), Olley and Pakes (1996) (Columns 3-4), and Wooldridge (2009) (Columns 5-6). All TFP estimates are normalized to have mean 0 and standard deviation 1. All regressions include firm, region-year and 4-digit industry-year fixed effects. $X_{it} = 1(\text{Broadband})_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Table A2: Impact on Wage Bill Across Worker Types

	Total		Managers		Prof./Tech.		Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Unconditional								
1(Broadband)	0.03***	0.37***	0.01***	0.03	0.00***	0.02	0.01***	0.31***
	(0.01)	(0.12)	(0.00)	(0.04)	(0.00)	(0.02)	(0.00)	(0.07)
Y Mean	0.82	0.82	0.21	0.21	0.07	0.07	0.43	0.43
Panel B: Fraction of wL								
1(Broadband)	0.00	0.00	0.00	-0.02	0.00*	-0.00	-0.01**	0.02
	(.)	(.)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)	(0.03)
Y Mean	1.00	1.00	0.31	0.31	0.09	0.09	0.59	0.59
N	23	23	10679	10679	10684	10684	10695	10695
No. of Firms	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables is the total wage bill of a firm (Columns 1-2), and expenditure on managers (Columns 3-4), professional and technician workers (Columns 5-6), and production workers (Columns 7-8). Panel A reports the unconditional regression, while Panel B reports as a fraction of the total wage bill. All regressions include firm, region-year and 4-digit industry-year fixed effects. $1(\text{Broadband})_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Table A3: Impact on Managerial Worker Contracts

	Payroll		Contract		Third Party	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unconditional						
1(Broadband)	0.70***	2.21	0.09	-0.99	0.52***	-0.36
	(0.21)	(2.38)	(0.13)	(1.79)	(0.13)	(1.48)
Y Mean	12.51	12.51	4.04	4.04	2.42	2.42
Panel B: Fraction of Total Workers						
1(Broadband)	-0.00	0.02	0.00	0.04	0.00**	-0.02
	(0.00)	(0.05)	(0.00)	(0.04)	(0.00)	(0.02)
Y Mean	0.69	0.69	0.19	0.19	0.06	0.06
N	10650	10650	10650	10650	10650	10650
No. of Firms	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables are total managerial and administrative workers in a firm on permanent, salaried contracts (Columns 1-2), on temporary contracts hired directly by the firm (Columns 3-4), and on temporary contracts hired through third-party intermediaries (Columns 5-6). Panel A reports the unconditional regression, while Panel B reports as a fraction of total firm size. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p$<$0.1 ** is p$<$0.05 and *** is p$<$0.01.

Table A4: Impact on Professional and Technician Worker Contracts

	Payroll		Contract		Third Party	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unconditional						
1(Broadband)	0.18	-3.46*	-0.11	-0.55	0.08	-0.95
	(0.12)	(1.79)	(0.08)	(0.96)	(0.05)	(0.75)
Y Mean	5.18	5.18	1.80	1.80	0.73	0.73
Panel B: Fraction of Total Workers						
1(Broadband)	0.00	-0.04	0.00	0.08	0.00	-0.05*
	(0.01)	(0.06)	(0.00)	(0.06)	(0.00)	(0.03)
Y Mean	0.65	0.65	0.22	0.22	0.05	0.05
N	8049	8049	8049	8049	8049	8049
No. of Firms	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables are total professional and technician workers in a firm on permanent, salaried contracts (Columns 1-2), on temporary contracts hired directly by the firm (Columns 3-4), and on temporary contracts hired through third-party intermediaries (Columns 5-6). Panel A reports the unconditional regression, while Panel B reports as a fraction of total firm size. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p$<$0.1 ** is p$<$0.05 and *** is p$<$0.01.

Table A5: Impact on Production Workers

	Payroll		Contract		Third Party	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unconditional						
1(Broadband)	0.81**	8.84*	0.38	6.75**	0.70**	5.33
	(0.32)	(4.52)	(0.30)	(3.44)	(0.29)	(3.41)
Y Mean	22.80	22.80	10.94	10.94	9.07	9.07
Panel B: Fraction of Total Workers						
1(Broadband)	0.01	-0.02	-0.01*	0.04	0.00	-0.01
	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)	(0.03)
Y Mean	0.62	0.62	0.25	0.25	0.12	0.12
N	10964	10964	10964	10964	10964	10964
No. of Firms	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variables are total production workers in a firm on permanent, salaried contracts (Columns 1-2), on temporary contracts hired directly by the firm (Columns 3-4), and on temporary contracts hired through third-party intermediaries (Columns 5-6). Panel A reports the unconditional regression, while Panel B reports as a fraction of total firm size. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

Table A6: Impact on Domestic and Foreign Hiring of Professionals and Technicians

	Any		Total		Payroll		Contract		Third Party	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Domestic Prof./Tech. Workers										
1(Broadband)	0.02***	0.10	0.13	-4.98**	0.17	-3.58**	-0.11	-0.55	0.08	-0.95
	(0.01)	(0.06)	(0.17)	(2.34)	(0.12)	(1.78)	(0.08)	(0.96)	(0.05)	(0.75)
Y Mean	0.61	0.61	7.77	7.77	5.16	5.16	1.79	1.79	0.73	0.73
Panel B: Foreign Prof./Tech. Workers										
1(Broadband)	0.00	0.04*	0.01	0.12*	0.01	0.12**	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.02)	(0.01)	(0.07)	(0.01)	(0.05)	(0.00)	(0.02)	(0.00)	(0.04)
Y Mean	0.02	0.02	0.04	0.04	0.02	0.02	0.01	0.01	0.00	0.00
N	10964	10964	10964	10964	10964	10964	10964	10964	10964	10964
No. of Firms	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: The outcome variable a binary variable of whether a firm hires any professional or technician (Columns 1-2), total hires (Columns 3-4), and whether they are hired on payroll (Columns 5-6), contract (Columns 7-8), or through a third party (Column 9-10). Panel A reports domestic hires, while Panel B reports foreign ones. All regressions include firm, region-year and 4-digit industry-year fixed effects. 1(Broadband)$_{it}$ that takes the value 1 for all years after which a firm i first reports using broadband internet and 0 otherwise. Y mean is the mean of the outcome variable. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

B Mathematical Proofs

B.1 Proof for Proposition 1

The impact on firm output can be given implicitly by how marginal revenues and costs change with broadband adoption. Differentiating Equation (4) we get:

$$MR'(q^*) = \underbrace{\lambda_x'(B)\mathcal{R}_q}_{\text{Market access}} + \lambda_x \Big(\underbrace{\mathcal{R}_{qq}\frac{dq^*}{dB}}_{\text{Production}} + \underbrace{\mathcal{R}_{q\mathcal{I}}\frac{d\mathcal{I}}{dB}}_{\text{G.E. Demand}} \Big) \tag{B1}$$

$$MC'(q^*) = = \underbrace{C_{qq}\frac{dq^*}{dB}}_{\text{Production}} + \underbrace{\nabla_{\widetilde{\mathbf{w}}} C_q^\top \frac{d\widetilde{\mathbf{w}}}{dB}}_{\text{Eff. Input Prices}} \tag{B2}$$

Since $\widetilde{\mathbf{w}} = \boldsymbol{\lambda}(B) \circ \mathbf{w}$, the change in the marginal cost of an input i is driven implicitly by *both* the direct effect of lowering frictions in accessing it (λ_i) in partial equilibrium; and an indirect effect of changing the marginal cost itself in general equilibrium w_i, i.e.,

$$\frac{d\widetilde{\mathbf{w}}}{dB} = \text{diag}(\boldsymbol{\lambda})\frac{d\mathbf{w}}{dB} + \text{diag}(\mathbf{w})\,\boldsymbol{\lambda}'(B). \tag{B3}$$

Equating (B1) and (B2) and rearranging yields Equation (5). ■

B.2 Proof for Proposition 2

The proof for Proposition 2 follows from using the duality of production identities. The Marshallian demand for inputs can be expressed as a function of optimal Hicksian demand (from Equation 3) i.e., $\mathbf{x}^*(B) = \mathbf{h}(q^*(B), \widetilde{\mathbf{w}}(B), \Theta(B))$. Differentiating with respect to B using the chain rule gives Equation (7). ■

B.3 Firm Production (Lemma 1)

Note from the VES production function that:

$$\frac{dq}{dl_i} = \left[a_i l_i^{\phi} + \frac{1}{2}\sum_j b_{ij}(l_i l_j)^{\frac{\phi}{2}} \right] \phi l_i^{-1} = \phi q_i l_i^{-1} \tag{B4}$$

From the FOC of the profit maximization problem we have:

$$\widetilde{w}_i = \frac{\sigma}{1+\sigma}\frac{x}{y} \cdot \frac{1}{\phi}\frac{y}{q} \;\; \phi q_i l_i^{-1} \tag{B5}$$

$$\widetilde{w}_i l_i = \frac{\sigma}{1+\sigma} \cdot \frac{q_i}{q} \cdot x \tag{B6}$$

Note that the expenditure shares for an input i (denoted by κ_i) can then be given by:

$$\kappa_i = \frac{\widetilde{w}_i l_i}{\sum_i \widetilde{w}_i l_i} = \frac{q_i}{q} \tag{B7}$$

$$\sum_i \widetilde{w}_i l_i = \frac{\sigma}{1+\sigma} x \tag{B8}$$

$$\Rightarrow \pi = \frac{x}{1+\sigma} = \frac{1}{\sigma}\sum_i \widetilde{w}_i l_i \tag{B9}$$

The unit cost of producing one unit of output, denoted by c will be given by: $c = \frac{\sum_i \widetilde{w}_i l_i}{y} = z^{-1} c_q$, where $c_q = \min_{l_i} \sum_i \widetilde{w}_i l_i \;\; s.t. \;\; q = 1$. In other words, the profit maximization problem of the firm can be written as:

$$\pi = A y^{\frac{\sigma}{1+\sigma}} - cy \qquad \left(\text{where: } A = \lambda_x^{\frac{1}{1+\sigma}} P_m C_m^{\frac{1}{1+\sigma}}\right)$$

Taking the first order condition and rearranging we get:

$$\begin{aligned}
cy &= \frac{\sigma}{1+\sigma} A y^{\frac{\sigma}{1+\sigma}} \\
y &= \left[\frac{\sigma}{1+\sigma} \cdot \frac{z}{c_q / P_m}\right]^{1+\sigma} \lambda_x C_m \\
p &= \left(\frac{y}{\lambda_x C_m}\right)^{\frac{-1}{1+\sigma}} P_m \;\; = \frac{1+\sigma}{\sigma} \cdot \frac{c_q}{z} \qquad \text{(from firm demand)} \\
x &= \left(\frac{p(z)}{P_m}\right)^{-\sigma} \;\; \lambda_x P_m C_m
\end{aligned}$$

■

B.4 Aggregate TFP and Sales (Lemma 2)

TFP. Average TFP, defined as the productivity of the "representative firm" in the economy can be given by:

$$\begin{aligned}
\overline{Z}^{\sigma} &= E(z^{\sigma}|z \geq z_e) = \int_{z_e}^{\infty} z^{\sigma} \frac{dF(z)}{1-F(z_e)} \\
&= \int_{z_e}^{\infty} z^{\sigma} \frac{\theta z^{-\theta-1}}{z_e^{-\theta}} dz = \theta z_e^{\theta} \int_{z_e}^{\infty} z^{\sigma-\theta-1} dz \\
&= \frac{\theta z_e^{\theta}}{\theta-\sigma} \cdot z_e^{\sigma-\theta} = \frac{z_e^{\sigma}}{1-\widetilde{\theta}} \\
\Rightarrow \overline{Z} &= (1-\widetilde{\theta})^{\frac{-1}{\sigma}} z_e
\end{aligned}$$

Given this, total or aggregate TFP can be given by:

$$Z = (1-F(z_e)) \cdot E(z^{\sigma}|z \geq z_e) = (1-\widetilde{\theta})^{-1} z_e^{\sigma-\theta} \tag{B10}$$

Sales. From Equation (15), note that $x^{(b)} = \psi_x^{(b)} z^{\sigma}$. Therefore, we need to calculate aggregate TFP for adopters and non-adopters separately as follows:

$$\begin{aligned}
Z^{(0)} &= \int_{z_e}^{z_b} z^{\sigma} \cdot \theta z^{-\theta-1} dz = \frac{\theta}{\theta-\sigma} \left[z_e^{\sigma-\theta} - z_b^{\sigma-\theta} \right] = \left[1 - \xi^{1-\widetilde{\theta}} \right] \cdot \frac{z_e^{\sigma-\theta}}{1-\widetilde{\theta}} \\
Z^{(1)} &= \int_{z_b}^{\infty} z^{\sigma} \cdot \theta z^{-\theta-1} dz = \frac{\theta}{\theta-\sigma} z_b^{\sigma-\theta} = \xi^{1-\widetilde{\theta}} \cdot \frac{z_e^{\sigma-\theta}}{1-\widetilde{\theta}}
\end{aligned}$$

Aggregate sales are then given by: $X = \psi_x^{(0)} Z^{(0)} + \psi_x^{(1)} Z^{(1)}$.

Input Demand. Re-arranging Equation (13), we have:

$$l_i^{(b)}(z) = \left(\frac{\sigma}{1+\sigma} \right) \left(\frac{\kappa_i^{(b)}}{\lambda_i^{(b)}} \psi_x^{(b)} \right) \frac{z^{\sigma}}{w_i}. \tag{B11}$$

We can then aggregate this similar to the sales above to get the expression in Lemma 2.

■

B.5 Entry and Adoption Thresholds

From Equation (16), a firm will adopt broadband as long as:

$$\begin{aligned}\pi^{(1)}(z) = \frac{\psi^{(1)} z_b^{\sigma}}{1+\sigma} - F_b &\geq \pi^{(0)}(z) = \frac{\psi^{(0)} z_b^{\sigma}}{1+\sigma} \\ z_b^{\sigma} &= \frac{(1+\sigma)F_b}{\psi^{(1)} - \psi^{(0)}}\end{aligned} \tag{B12}$$

Firms enter by paying cost F_e. Aggregating across all firms, total profits in the economy (Π) can be given by:

$$\begin{aligned}\Pi &= \frac{X}{1+\sigma} - [1 - F(z_b)]F_b \\ &= \frac{X}{1+\sigma} - z_b^{-\theta} F_b \\ &= \frac{X}{1+\sigma} - \xi F_b \cdot z_e^{-\theta}\end{aligned}$$

Free entry implies that expected (average) profits equal to F_e i.e., : $\Pi/(1 - F(z_e)) = F_e$, which implies:

$$\begin{aligned}F_e &= \left[\frac{X}{1+\sigma} - \xi F_b \cdot z_e^{-\theta}\right] \cdot z_e^{\theta} \\ F_e + \xi F_b &= \frac{\Psi_x z_e^{\sigma}}{(1+\sigma)(1-\widetilde{\theta})} \\ z_e^{\sigma} &= \frac{(1-\widetilde{\theta})(1+\sigma)(F_e + \xi F_b)}{\Psi_x}\end{aligned} \tag{B13}$$

■

B.6 Aggregate Price Index (P_m)

The aggregate price index for manufacturing is determined by the composition and mass of firms, and by the cutoffs $\{z_e, z_b\}$. Using the fact that the mass of firms is equal to 1, this can be calculated as follows:

$$P_m = \left[\int_{z_e}^{\infty} \lambda_x p(z)^{-\sigma} dF(z)\right]^{\frac{1}{\sigma}} = \left[\frac{\int_{z_e}^{z_b} \lambda_x^{(0)} p^{(0)}(z)^{-\sigma} dF(z) + \int_{z_b}^{\infty} \lambda_x^{(1)} p^{(1)}(z)^{-\sigma} dF(z)}{1 - F(z_e)}\right]^{-\frac{1}{\sigma}}$$

In other words, P_m is the price charged by a "representative" firm, which is a weighted average across prices charged by firms in the economy. From Equation (14), define:

$$A^{(b)} = \left(\frac{1+\sigma}{\sigma}\right)^{-\sigma} \lambda_x^{(b)} (c^{(b)})^{-\sigma}$$

Aggregating over the price indices separately between non-adopters and adopters:

$$\int_{z_e}^{z_b} \lambda_x^{(0)} p^{(0)}(z)^{-\sigma} dF(z) = A^{(0)} Z^{(0)\sigma} = \left[1 - \xi^{1-\widetilde{\theta}}\right] \cdot \frac{A^{(0)} z_e^{\sigma-\theta}}{1-\widetilde{\theta}}$$
$$\int_{z_b}^{\infty} \lambda_x^{(1)} p^{(1)}(z)^{-\sigma} dF(z) = A^{(1)} Z^{(1)\sigma} = \xi^{1-\widetilde{\theta}} \cdot \frac{A^{(1)} z_e^{\sigma-\theta}}{1-\widetilde{\theta}}$$

Define: $C_q = \left[(1-\xi^{1-\widetilde{\theta}})\lambda_x^{(0)} (c_q^{(0)})^{-\sigma} + \xi^{1-\widetilde{\theta}} \lambda_x^{(1)} (c_q^{(1)})^{-\sigma}\right]^{\frac{-1}{\sigma}}$. Substituting it back, we have:

$$P_m^{-\sigma} = \left(\frac{1+\sigma}{\sigma}\right)^{-\sigma} \cdot C_q^{-\sigma} \cdot \frac{1}{1-\widetilde{\theta}} \cdot \frac{z_e^{\sigma-\theta}}{z_e^{-\theta}}$$
$$\Rightarrow P_m = \left(\frac{1}{1-\widetilde{\theta}}\right)^{-\frac{1}{\sigma}} \cdot \left(\frac{1+\sigma}{\sigma}\right) \cdot \frac{C_q}{z_e}$$

Putting it all together and noting from Lemma 2 that $\overline{Z} = \left(1-\widetilde{\theta}\right)^{-\frac{1}{\sigma}} z_e$, we have:

$$P_m = \left(\frac{1+\sigma}{\sigma}\right) \cdot \frac{C_q}{\overline{Z}}$$

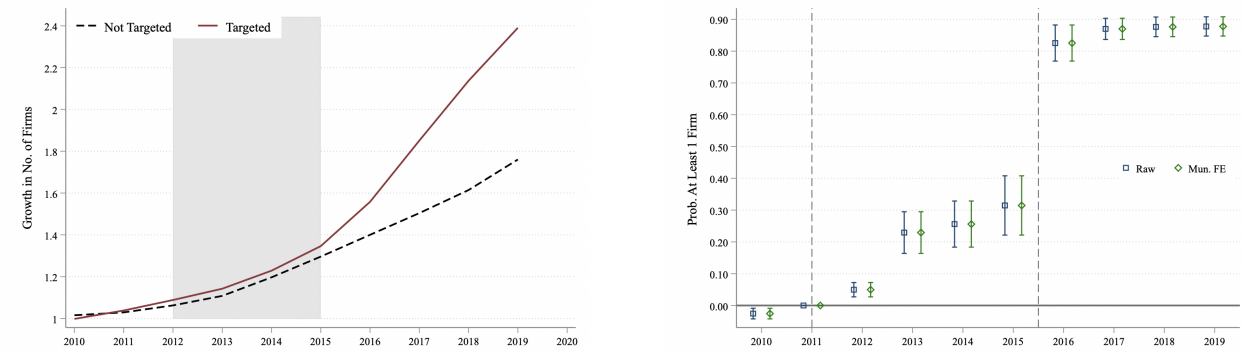
■

C Broadband Expansion and Adoption: A Discussion

C.1 Proyecto Nacional de Fibra Óptica (PNFO)

At the beginning of 2010, the Colombian government, under the National Development Plan of 2010-14 promoted the access and use of ICT under the Vive Digital plan.[11] As a part of this initiative, the Proyecto Nacional de Fibra Óptica (PNFO) or the National Optical Fiber Network (NOFN) expansion program was launched, which targeted broadband expansion to 788 municipalities by 2013-2014. PNFO consisted of planning, installing, and operating fiber optic services in these municipalities with an aim to extend high-speed internet to regions that had historically been underserved by private providers. The selection of municipalities was based primarily on geographic coverage goals and technical feasibility, bringing fiber backhaul to remote or peripheral areas.

Figure C1: Expansion in Connections and Firms After PNFO



(a) Growth in Firms

(b) Growth in Connections

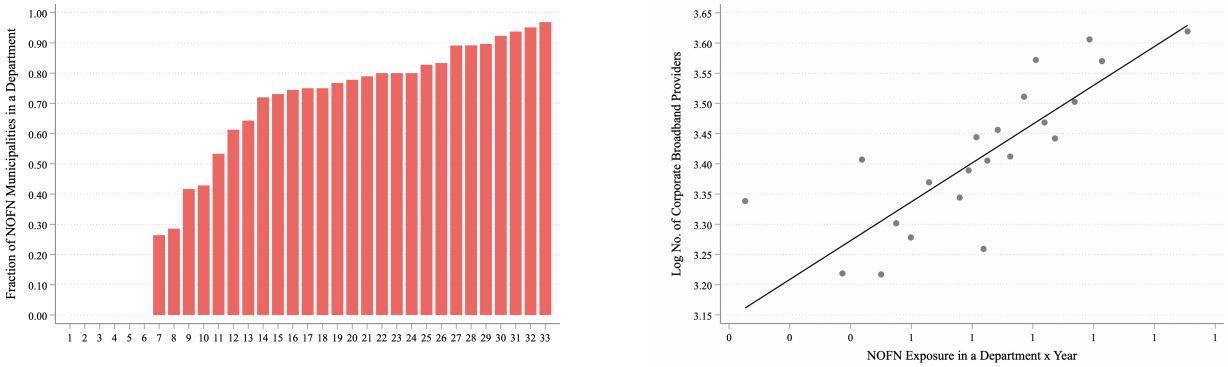
Notes: The above figures plot the growth in the number of firms providing broadband to businesses (Figure a) and their broadband connections (Figure b) from 2010-20. The solid red and dash black lines represent the averages for targeted and non-targeted municipalities respectively. The shaded area shows the period of the PNFO program.

Figure C1 plots the growth in the number of corporate broadband providers (Figure C1(a)) and corresponding connections (Figure C1(b)) between 2010-20. The solid red lines show the growth in municipalities targeted by PNFO, while the dash black lines show those that were not. Clearly, targeted municipalities experienced faster growth in broadband providers, resulting in a faster growth in demand for connections as well.

While the variation in the PNFO is across municipalities, the EAM data is only available at the department level. For each department, we therefore calculate the fraction of munic-

[11] See details on the Vive Digitial Initiative here.

Figure C2: PNFO Variation Across Colombian Departments



(a) Frac. Targeted Municipalities (b) Targeted Municipalities and Providers

Notes: Figure (a) plots the distribution of the fraction of municipalities within a department that were targeted by PNFO. Each observation in Figure (b) is a department-year. It shows the correlation between the log number of firms who provide corporate broadband connections and a time trend of the fraction of targeted municipalities. We control for the fraction of targeted municipalities and a year fixed effect.

ipalities in a department that were targeted by PNFO (ξ_d). As Figure C2(a) shows, there is a significant variation: some departments have no targeted municipalities, while others have over two-thirds. This also correlates strongly with the expansion in the number of broadband providers over time in a department as well. To see this, we regress:

$$\ln N_{dt} = \alpha_t + \underset{(0.102^{***})}{\beta \xi_d \times t} + \gamma \xi_d + \varepsilon_{dt}$$

where $\ln N_{dt}$ is the ISH number of broadband providers in a department d in year t. As Figure C2(b) reports, there is a strong positive correlation.

C.2 Construction of the Instrument

Our preferred instrument in the paper interacts the log number of firms that offer broadband internet in a region r and year t with the lag internet exposure in an industry-year in year $t-1$. In that sense, our instrument acts like a "shift-share" instrument in the spirit of Borusyak et al. (2022) and Borusyak et al. (2025). Essentially, this interaction captures "shifts" in supply-side variation, while lagged "exposure" intensity. In line with their guidance, therefore, we consider multiple constructions and report the first-stage results in Table C1.

First, in Columns (1)-(3) we use our preferred supply-side shift (log number of firms), but vary the lag from $t-1$ to $t-3$. Columns (4)-(6) uses the expansion in log firms pro-

Table C1: Robustness of the First Stage With Alternate Instruments

	1(Broadband Internet)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Ln(No. of Firms)						
Instrument	0.04***	0.02***	0.01***	0.05***	0.03***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F-Stat	247.29	80.29	7.07	367.15	111.23	9.49
R2	0.72	0.72	0.73	0.72	0.72	0.73
Panel B: Frac. of NOFN Municipalities						
Instrument	0.27***	0.16***	0.06***	0.30***	0.18***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
F-Stat	218.18	76.97	13.07	271.87	90.19	14.54
R2	0.72	0.72	0.73	0.72	0.72	0.73
N	93098	84492	74995	93098	84492	74995
Firms	10964	10638	10232	10964	10638	10232
Sample	LOU	LOU	LOU	All Firms	All Firms	All Firms
Exp. Lag	T-1	T-2	T-3	T-1	T-2	T-3

Notes: The above table shows the first-stage across a variety of instruments that varies by the supply-side shift and the exposure lag that varies sequentially from $t-1$ to $t-3$. Columns (1)-(3) use log firms that provide broadband services to firms in a region-year. Columns (4)-(6) use log of number of firms that provide residential internet services. Columns (7)-(9) use the fraction of municipalities in a department that were targeted under the PNFO expansion. Column (1) is our preferred specification used in the baseline. Standard errors are clustered at the firm level. * is p<0.1 ** is p<0.05 and *** is p<0.01.

viding residential broadband internet instead. Lastly, in Columns (7)-(9) we leverage an infrastruction expansion plan under the National Fiber Optic Network (NOFN) exposure.

The results provide three insights: (i) the sample size drops by around 10 thousand observations each year; (ii) the coefficient remains statistically significant, but drops in magnitude with higher lags; (iii) the F-stat, while over 300 in Column (1) drops to 100 and 12 with subsequent lags.

These are all consistent with Borusyak et al. (2022), who note: *"...while fixing exposure shares is useful for isolating time-varying shocks, lagging shares by many periods is likely to make the shift-share instrument less predictive of treatment, thereby reducing panel SSIV power."* In such cases, they advocate the use of *change* in the expsoure shares over time, something that our industry-year and region-year fixed effects implicitly incorporate.

C.3 An Event Study of Adoption

A potential concern with our identification strategy is that firms may select into broadband adoption based on anticipatory trends in firm performance. To test this, we create a variable D_{it}, which is the the number of years relative to the year t in which a firm i first reports adopting broadband internet. For example, $D_{it} = -d$ is d years before a firm i adopts high-speed internet and $D_{it} = +d$ is d years after. We restrict the observations to $d = \{-5, +7\}$ and estimate the following specification:

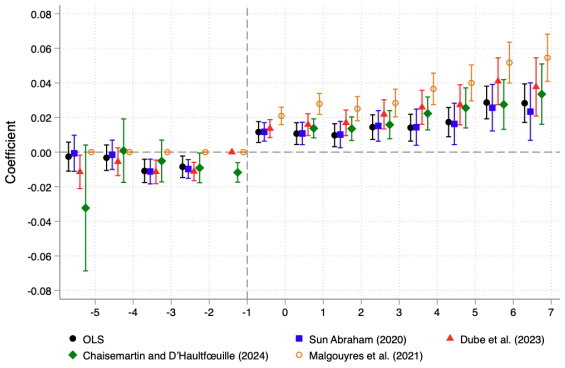
$$Y_{it} = \alpha_i + \alpha_t + \sum_{d=-5}^{d=7} \beta_d 1(D_{it} = d) + \varepsilon_{it} \tag{B14}$$

where Y_{it} are a set of firm-level outcomes such as value of production, revenues, costs, value-added, etc., α_i is a firm fixed effect that controls for all observable and unobservable time-invariant characteristics of the firm, α_t is a year fixed effect that controls for all observable and unobservable changes over time that are common to all firms. We cluster standard errors at the firm level.

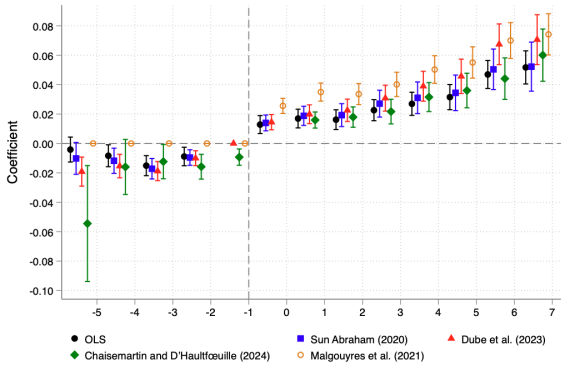
Figures C3 and C4 report the plots from the above specification across firm outcomes, ranging from: (i) fraction of workers using computers (Figure C3(a)); (ii) fraction of workers using the internet (Figure C3(b)); (iii) real capital expenditure (Figure C3(c)); (iv) total workers (Figure C3(d)); (v) real value of production (Figure C4(a)); (vi) real costs of production (Figure C4(b)); and (vii) real value-added (Figure C4(c)). We see across all these variables that there are no (or small) statistically significant differences between firms that do and do not adopt broadband internet prior to their adoption. However, significant differences emerge in firm performance after adoption and continue to strengthen over time.

Given the staggered adoption of broadband internet across firms, we redo these figures using more recent advances in this literature to check the robustness of our analysis. First, we show that including region-year and industry-year fixed effects does not alter the results. We also show robustness of these estimates to various other approaches developed in the literature by Sun and Abraham (2021), Dube et al. (2023), De Chaisemartin and d'Haultfoeuille (2024), and Malgouyres et al. (2019).

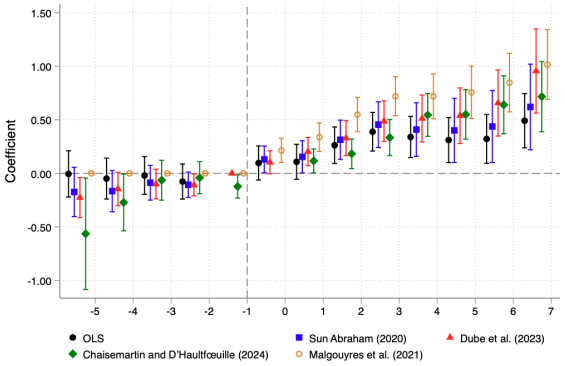
Figure C3: Impact of Internet Adoption on ICT Usage, Labor, and Capital



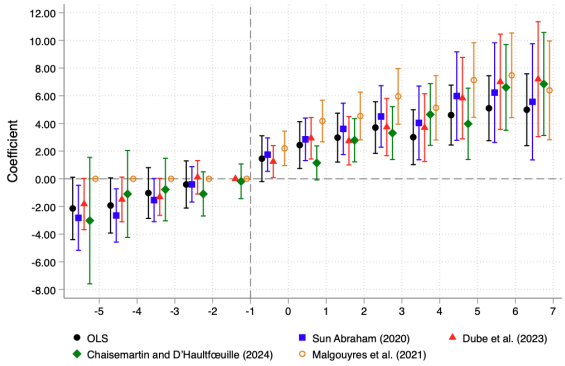
(a) Frac. Workers Using Computers



(b) Frac. Workers Using Internet



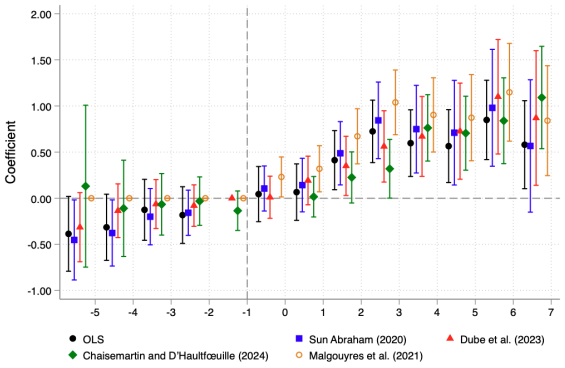
(c) Real K



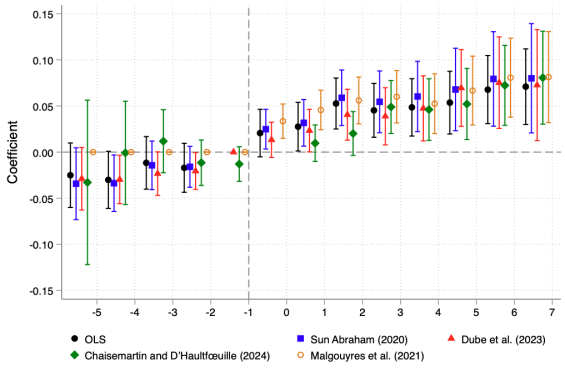
(d) Total Workers

Notes: The above figures plot the regression coefficients from various specifications for a set of firm-level outcomes. These include OLS estimates with region-year and industry-year fixed effects (black dots), along with approaches developed by Sun and Abraham (2021) (blue squares), Dube et al. (2023) (red triangles), De Chaisemartin and d'Haultfoeuille (2024) (green diamonds), and Malgouyres et al. (2019) (oranges circles). The horizontal axis shows years relative to the year in which a firm adopts broadband internet ($t = 0$). $t - 1$ is used as the reference year that is omitted from the regression. All outcome variables are windsorized at the top and bottom 5th percentiles. All regressions include firm and year fixed effects. Standard errors are clustered at the firm-level and 90% confidence intervals around the point estimates are reported in the figures.

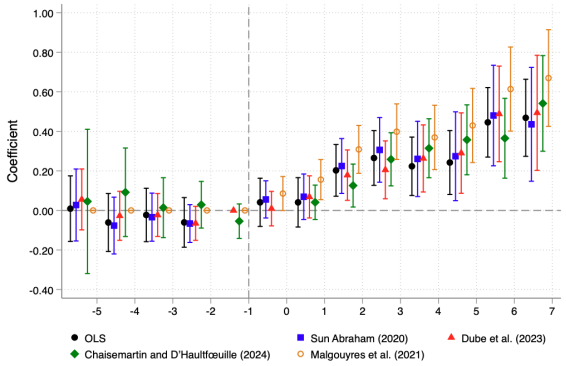
Figure C4: Impact of Internet Adoption on Firm Performance



(a) Real Value of Production



(b) Real Costs of Production



(c) Real Value Added

Notes: The above figures plot the regression coefficients from various specifications for a set of firm-level outcomes. These include OLS estimates with region-year and industry-year fixed effects (black dots), along with approaches developed by Sun and Abraham (2021) (blue squares), Dube et al. (2023) (red triangles), De Chaisemartin and d'Haultfoeuille (2024) (green diamonds), and Malgouyres et al. (2019) (oranges circles). The horizontal axis shows years relative to the year in which a firm adopts broadband internet ($t = 0$). $t - 1$ is used as the reference year that is omitted from the regression. All outcome variables are windsorized at the top and bottom 5th percentiles. All regressions include firm and year fixed effects. Standard errors are clustered at the firm-level and 90% confidence intervals around the point estimates are reported in the figures.