Assessing the Green Digital Transition: Evidence from Input-Output Networks

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December 9, 2025

Abstract

To what extent does digitalization of inputs decrease greenhouse gas emissions? Taking an economy-wide perspective exploiting input-output linkages, this paper estimates the impact of downstream sectors' adoption of digital inputs on greenhouse gas emissions. We develop a production-function model to understand the potential sources of efficiency gains from input digitalization, and test it using OECD inter-country input-output data across 45 sectors in 76 countries between 1995-2019. We find mixed evidence for the impact of digital adoption on emissions. Interactive fixed effects models, in addition to a shift-share instrumental variables strategy that exploits China's rise as a global digital exporter, largely suggests *increases* in overall emissions. Using subnational input-output tables across US states, alongside firm-level data, as alternative sources of variation, we continue to find null or adverse effects of digitalization on emissions. The results appear to be driven by rebound effects together with negligible or negative efficiency improvements. Scope-level emissions data further suggest that digitalization shifts the location of emissions rather than reducing them overall.

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1 Introduction

The idea that increasing the use of digital technologies as input across all sectors can reduce greenhouse gas (GHG) emissions and accelerate the green transition has gained significant traction in the public debate. Efficiency gains through optimized production processes are expected to reduce environmental externalities across whole industries. Digital applications such as dynamic line rating (DLR) for energy transmission, or automation technologies to improve the maintenance of machines and infrastructure assets, saving on energy and capital costs, are often mentioned (Calvino et al., 2025). Such beliefs have been widely embraced from business leaders to think tanks and government ministers, whereby carbon taxes and green subsidies can steer directed technical change towards digital technologies for sustainable growth (Acemoglu et al., 2014; Aghion et al., 2016; Hémous and Olsen, 2021; Dechezleprêtre and Hémous, 2022).[1] Notably, the World Economic Forum recently claimed that "digital solutions can reduce global emissions by up to 20 percent".[2]

Despite the fanfare behind this green and digital "twin" transition, there is highly mixed evidence documenting whether, and under which circumstances, digitalization – the process of producers integrating digital technologies into their operations – may indeed have such virtuous environmental impacts (Lange et al., 2020; Bonfiglioli et al., 2025). The most recent Intergovernmental Panel on Climate Change (IPCC) report states that "at present, the understanding of both the direct and indirect impacts of digitalisation on energy use, carbon emissions and potential mitigation is limited. If not appropriately governed, digitalisation can have adverse side-effects" (Blanco et al., 2022). As for their direct effect, Figure 1 shows, in a sample of 76 countries over the last 25 years using data from the OECD, that total production emissions from digital inputs has grown on par with their importance in productive sectors. The foremost question is thus whether digitalization has generated genuine environmental gains across the economy.

This paper aims at rigorously evaluating the impact of the increased digitalization of the economy that occurred worldwide since the 1990s on sector-level emissions via an input-output approach. Literature in environmental economics has recognized the need to decompose the sources of emissions from economic activities in terms of scale, composition and technique effects (Levinson, 2009; Lange et al., 2020; Bonfiglioli et al., 2025). To guide the empirical analysis along these terms, we first construct a simple reduced-form production function model, in which there is a choice between digital and residual (i.e. non-digital) inputs, and the share of digital inputs may

[1] Jean-Noël Barrot, French Minister for the Digital Transition and Telecommunications (2022-2024) claimed "Our society must successfully undertake two major transitions: the ecological transition and the digital transition. And it is imperative that the two be tackled together" (ARCEP, 2023). Business leaders have also latched onto digitalization as a strategy for reducing emissions: French business executive Jean-Pascal Tricoire, former CEO of Schneider Electric, claimed "To build collective prosperity we need to prioritize innovation and cut carbon emissions. Digitalization will play a key role in this" (CLG Europe, nd).

[2] See *'Digital solutions can reduce global emissions by up to 20 percent. Here's how'* from the World Economic Forum (2022). A recent report of the MIT Technology Review Insight Report (2023) also characterized digital technology as "the backbone of a net-zero emissions future". See also Blüm (2022) from the World Economic Forum.

affect the efficiency of the production process. We thus focus on emissions as resulting from specific input sources along the supply chain (Aghion et al., 2025) and how they map into final output, which further enables us to connect the model with the Greenhouse Gas Protocol emissions "scopes".

In a profit-maximizing setting, final emissions depend on the price and relative emissions content of each type of input (a "substitution effect"), as well as on the efficiency multiplier of digital inputs (an "efficiency gains effect"). The emissions content can be both direct (i.e. scope 1) or indirect (i.e. scopes 2 and 3), working through a firm's entire production line. The model motivates our empirical analysis by enabling us to decompose the effect of digitalization on total emissions in terms of intensity and output level elasticities, linking these margins explicitly to the relevant outcomes of interest: total emissions, total output, and emissions per unit of output. It also provides an intuitive interpretation of the well-known rebound and decoupling effects (Jevons, 1866; Lange et al., 2020; Calvino et al., 2025).

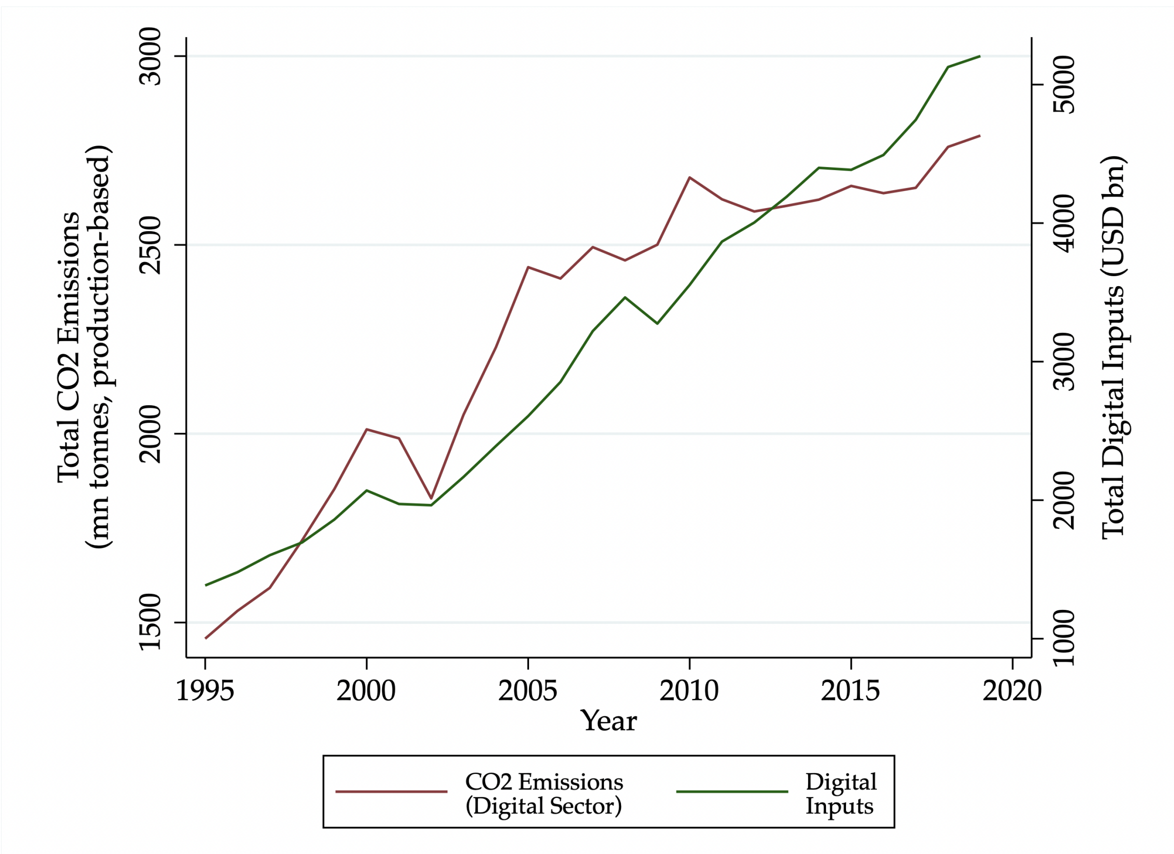


Figure 1: Global Digital Inputs and Emissions Content (1995-2019)

Note: data comes from the OECD's Inter-Country Input-Output (ICIO) tables and Greenhouse Gas Footprints data. The digital sector is comprised of 'Computer, electronic and optical equipment', 'Telecommunications' and 'IT and other information services'. Both series sum across 76 countries and these three digital sectors per year.

Our core empirical analysis draws on inter-country input–output (IO) tables across a broad set of developed and emerging economies. The main sample covers 76 countries across 45 sectors between 1995-2019, matched with sector-level GHG emissions from the Greenhouse Gas Footprints (GHGFP) data, both sourced from the OECD.[3] We first document several stylized facts regarding the centrality of the digital sector in the global economy, comprising 'computer, electronic and optical equipment', 'IT and other information services', and 'telecommunications' (Charpentier et al., 2023; Nose and Honda, 2023; Criscuolo et al., 2025). Although North American manufacturing largely dominated global supply chains in the mid-1990s, this has shifted rapidly to the digital sector today, especially from China.

Following the global expansion of digital technologies since the 1990s, our core identifying variation leverages the fact that different sectors within countries adopt digital inputs to different intensities at different times. Exploiting this within country-downstream sector variation, we hence assess the impact of digital input adoption as a share of total inputs on total emissions, output, and emissions per unit of output. Our core specification not only includes a country-downstream sector fixed effect, but we also flexibly control for other time varying trends at the country and sector level using interactive fixed effects. These initial results ultimately reveal *null* effects of digital input adoption on total emissions and, if anything, an increase in emissions per unit of output. When unpacking these results by scope, we only find strong evidence for an *increase* in scope 2 emissions, both overall and per unit of output.[4] These results continue to hold across a series of sensitivity checks, including alternative specifications such as deeper lag structures on digital adoption and an event study for dynamic effects, as we outline in the Appendix.

Although we control for various fixed effects interactively at the country, sector, and year level, the adoption of digital inputs is clearly an endogenous decision of producers. We might for example expect that sectors on a steeper efficiency improvement trajectory adopt digital inputs faster (Aklilu et al., 2024; Calvino et al., 2024). We address this using a "shift-share" instrument to generate quasi-exogenous variation in digital input intensity within country-sectors. Our instrument builds on two strands of literature. First, research on endogenous production networks suggests that the initial network structure can be exploited to predict input diffusion, and so we use sectors' initial connectedness to digital via the Leontief inverse as the "share" (Acemoglu et al., 2012; Carvalho and Voigtländer, 2015; Criscuolo et al., 2025). Second, we develop a "shift" variable similar to Acemoglu et al. (2016a), exploiting exposure to China's rise as a global digital exporter via upstream and downstream sources, a finding we label the "China digital shock".

None of our shift-share results support the idea that digitalization contributes to reducing emissions. Rather, our core estimates indicate a significant increase in emissions in both levels and per unit of output. When unpacking emissions by scope, the results point to higher emissions in levels, driven mostly by their scope 2 and 3 components, with a strong increase in scope 3 emissions

[3] We exclude 2020, as the start of the COVID-19 pandemic had stark effects on production, digital adoption and emissions. See for example Calvino et al. (2024).

[4] See a precise definition of scope 1, 2 and 3 emissions in Section 3.1.1 below.

per unit of output. The bottom line suggests that digitalization affects *where*, rather than whether, emissions occur. This in turn puts the focus squarely back on the emissions of upstream sectors, especially those driving the energy mix underpinning the consumption of digital inputs. We find these results are primarily driven through China's digital expansion working through country-sectors' suppliers, indicating that digital diffusion from this shock propagates downstream. Our estimates are also robust to weak instrument diagnostics, given we exploit China's export activity across trading partners globally versus a single national context (Autor et al., 2013b; Acemoglu et al., 2016b).

As an alternative source of variation, and to further address the issue of correlated unobservables, we also home in on the United States as a single country context, using state-level (i.e. sub-national) input-output tables. This allows us to measure digital input intensity and sector-level emissions across all 50 states in 64 sectors between 2012-2019, exploiting within state-sector variation (Ingwersen et al., 2022). Focusing on the United States also allows us to test alternative proxies for the digitalization of production, where we use a measure of digital-related human-capital (Brynjolfsson et al., 2024). Consistent with the global analysis, none of our results show any significant connection between digital input adoption and emissions from production-based activities. If anything, our estimates again point to increases in emissions, output and emissions per unit of output, although these are imprecisely estimated.

Finally, as the most precise and granular source of identifying variation available, we provide firm-level results using data from the S&P Global's Trucost Environmental database, which covers 5,300 unique firms across 53 countries since 2010. We first measure digital adoption based on country-downstream sector-level shifts, weighted by initial firm size (Nose and Honda, 2023). For a subset of several hundred American firms, we also use capitalized software costs as a share of total assets, in addition to direct supplier-to-customer linkages from suppliers in the digital sector (Carvalho and Voigtländer, 2015). Exploiting within-firm variation, we again find a broad suite of null effects, both in terms of output and by emissions scope. Our results are reminiscent of those in Bolton et al. (2023), who find that firms producing more climate-related patents do not exhibit lower CO2 emissions.[5]

We contribute to the growing literature that nuances the positive impact of digitalization on environmental outcomes (Lange et al., 2020; Bonfiglioli et al., 2025; Calvino et al., 2025). We do so by providing a comprehensive assessment of the net consequences of digital input intensity on GHG emissions, exploiting several different sources of variation globally, sub-nationally and at the firm-level. While the economics literature has documented the effects of digital technology penetration across a range of outcomes (Goldfarb et al., 2015; Goldfarb and Tucker, 2019; Greenstein, 2020; Hjort and Tian, 2021), comparatively less attention has been paid to environmental impacts.[6] That said, a volume of more recent studies across various fields have focused on the environmental

[5] Hege et al. (2025) nuance this result by showing positive impacts on innovators' customer firms.

[6] Foster et al. (2025) is a meta-analysis of the general literature on infrastructure impact, including the digital sector.

repercussions of specific digital investments and interventions (Hao et al., 2023; Roussilhe et al., 2023; Zeng and Yang, 2023; Istrate et al., 2024; Yi et al., 2024; Bai et al., 2025).

While there are many possible approaches to assessing the "twin transition", our core contribution is the focus on supply-chains and use of input-output techniques (Charpentier et al., 2023; Criscuolo et al., 2025). Theoretically, if digital adoption reduces GHG emissions via efficiency gains within sectors, and this output is then used as input by another sector, then digitalization should have knock-on consequences by decreasing marginal emissions downstream. However, if rebound effects are such that producers who digitalize end up demanding more gross inputs, marginal emissions may still increase. We connect these ideas to our reduced-form empirics by focusing on emissions "scopes", with our global evidence suggesting scope 2 and 3 emissions increase non-negligibly in response to digital adoption. This underscores how the digitalization of production is by no means a sure-fire process of "greenification" (i.e. moving from dirty to cleaner varieties along the supply chain) (Aghion et al., 2025).

The use of input-output data and techniques also enables us to go some way in more credibly identifying the environmental consequences of digitalization.[7] Previous analyses have relied on cross-sectional time-series variation, either at the country, region or city level, to study the nexus between digital adoption and emissions (Shahbaz et al., 2022; Zeng and Yang, 2023; Bai et al., 2025). We contribute to the literature by focusing on sector-level and firm-level outcomes within countries via input-output analysis. Similar to Criscuolo et al. (2025), this allows us to exploit a more credible source of variation, given that different sectors and firms within countries likely adopt digital technologies differentially over time. Input-output techniques also allow us to generate sources of quasi-exogenous variation via a shift-share instrument to predict input-diffusion (Carvalho and Voigtländer, 2015). And while not the main focus of the paper, the "China digital shock" also adds a new angle to the broader China-shock literature, emphasizing global digital spillovers from China's economic rise additional to North American manufacturing displacement (Autor et al., 2013b, 2016; Acemoglu et al., 2016b).

Ultimately, the results uncovered by our analysis confirm that it is in no way a foregone conclusion that the ongoing process of digitalization of economic activities will have GHG emissions benefits. This yields a range of implications to consider on the digitalization-emissions debate. First, greening the sources of energy that support digital inputs appears to be a key enabling factor. Second, the case for digital technologies as a means to support environmental improvements cannot rely on a laissez-faire approach. While some digital inputs can potentially be "clean", in most cases ensuring that innovation and production are directed towards them is unlikely to happen unless the right public policies are put in place. Depending on the sectors and the nature of inputs available, these will take the form of different combinations of carbon taxes and research subsidies (Acemoglu et al., 2014; Aghion et al., 2016). Whether the policies supporting a green digital transition are enacted will also depend crucially on the political economy of the process,

[7] The use of input-output linkages to study environmental outcomes dates back at least to Leontief (1973).

and in particular the interactions between stakeholders holding "green" versus "brown" values (Besley and Persson, 2023).

2 Model

A representative profit-maximizing firm chooses a combination of inputs, x_{ij}, to produce output, Y_i.[8] Suppose there are S sectors, where $\mathcal{D}$ is the set of inputs belonging to the digital sector and $\mathcal{D}'$ represents all non-digital sectors. For simplicity, assume inputs are perfectly substitutable within digital and non-digital sectors, such that total digital inputs is captured by $D_i = \sum_{j \in \mathcal{D}} x_{ij}$ and total non-digital inputs is $N_i = \sum_{j \in \mathcal{D}'} x_{ij}$. We can further denote $X_i = D_i + N_i$ as total inputs, so $D_i = d_i X_i$, where d_i is the digital input share. Firm i in sector s has a CES production function, scaled by total productivity parameter, A_i:[9]

$$Y_i = A_i \left[\gamma D_i^{\xi} + (1-\gamma) N_i^{\xi}\right]^{\frac{1}{\xi}}, \tag{2.1}$$

with input productivity parameter $\gamma \in (0,1)$ and the elasticity of substitution is $\sigma = \frac{1}{1-\xi} \in (0, +\infty)$ where $\xi \in (-\infty, 1)$. We assume D_i and N_i are substitutes, such that $\sigma < 1$. Total digital inputs and non-digital inputs have respective aggregate prices, p_D and p_N.

Profit Maximization Denoting the price of outputs as p_Y, profit maximization for firm i is thus:

$$\max_{D_i, N_i} \pi_i(D_i, N_i) = p_Y A_i \left[\gamma D_i^{\xi} + (1-\gamma) N_i^{\xi}\right]^{\frac{1}{\xi}} - (p_D D_i + p_N N_i)$$

Taking the first order condition for profit maximization to find input demand functions, and taking their ratio, we have that:

$$\frac{D_i}{N_i} = \left[\frac{p_D}{p_N}\left(\frac{1-\gamma}{\gamma}\right)\right]^{\frac{1}{\xi-1}} \tag{2.2}$$

Optimal Input Mix Using the previous results, we can define the optimal digital input share for profit maximization as follows:

$$d_i = \frac{D_i}{D_i + N_i} = \frac{\left[\frac{p_D}{p_N}\left(\frac{1-\gamma}{\gamma}\right)\right]^{\frac{1}{\xi-1}}}{1 + \left[\frac{p_D}{p_N}\left(\frac{1-\gamma}{\gamma}\right)\right]^{\frac{1}{\xi-1}}} \tag{2.3}$$

Clearly, as the standard result, if digital input prices are cheaper relative to non-digital input prices, $p_D < p_N$, firms will lean towards a greater digital input combination as a share of total inputs. A reallocation towards digital inputs will also be more likely if $\gamma \to 1$.

[8] Given the representativity hypothesis, we use sector and firm interchangeably. The assumption can be relaxed with insights remaining similar.

[9] In Appendix C, we provide richer micro-foundations for the CES structure of the model, also incorporating inputs via trade with foreign trading partners.

Network Effects Additional to the (quantity) share of digital inputs, d_i, used in production, we can further define "technical coefficients", where input expenditure is normalized by total output, such that:

$$a_{ij} = \frac{p_j x_{ij}}{p_Y Y_i},$$

and p_j represents the price of individual inputs. Across all sectors, this gives rise to the standard technical coefficients matrix, $\mathbf{A}$, where each a_{ij} are elements. We can thus define the *Leontief inverse* as (Acemoglu et al., 2016a):

$$\mathbf{\Omega} = (\mathbf{I} - \mathbf{A})^{-1} \tag{2.4}$$

The entries of $\mathbf{\Omega}$ represent the total (direct and indirect) amount of input from sector i that is required to produce one unit of final output in downstream sector j, Ω_{ij}. In response to shocks, the Leontief inverse captures both the direct effects of the shock on a sector's input demand and the higher-order, equilibrium effects that propagate through the production network via all linkages.

Marginal Emissions Suppose inputs contain emissions per unit, ϕ_j, which are both direct based on firm activities and indirect based on purchased inputs. In the digital sector, we can thus define total emissions per unit of digital as $\tilde{\phi}_D = \phi_D + \sum_{j \in \mathcal{D}'} \phi_j \Omega_{ji}$, where ϕ_D are direct emissions per unit of digital and $\sum_{j \in \mathcal{D}'} \phi_j \Omega_{ji}$ represents all emissions embodied in the supply chain (i.e. across non-digital inputs). The analog for non-digital inputs is thus $\tilde{\phi}_N = \phi_N + \sum_{j \in \mathcal{D}} \phi_j \Omega_{ji}$. We can therefore think of $\phi_{\{D,N\}}$ as scope 1 emissions, and emissions from other inputs in the supply chain using entries of the Leontief inverse as scope 2 and 3 emissions, namely indirect emissions from other purchased inputs.

In addition to producing output, firms thus release total emissions from production, E_i, equal to the following:

$$E_i = \Delta(d_i) \left[\tilde{\phi}_D D_i + \tilde{\phi}_N N_i \right] \tag{2.5}$$

This is simply total emissions embedded in inputs, where $\tilde{\phi}_{\{D,N\}} \in \mathbb{R}_+$ refers to emissions per unit of input for respective input types, scaled by $\Delta(d_i) \in \mathbb{R}_+$, which captures a production efficiency multiplier in response to relative input shares.

We can rewrite equation (2.5) as:

$$E_i = \Delta(d_i) \left[\tilde{\phi}_N + (\tilde{\phi}_D - \tilde{\phi}_N) d_i \right] X_i \tag{2.6}$$

To find the total digital-emissions elasticity, we can take the derivative of the log of equation (2.6) with respect to the log of d_i, which yields the following:

$$\frac{\partial \ln E_i}{\partial \ln d_i} = d_i \Bigg(\underbrace{\frac{\partial \Delta(d_i)}{\partial d_i} \frac{1}{\Delta(d_i)}}_{\substack{\text{efficiency gains} \\ \text{effect}}} + \underbrace{\frac{\tilde{\phi}_D - \tilde{\phi}_N}{\tilde{\phi}_N + (\tilde{\phi}_D - \tilde{\phi}_N) d_i}}_{\text{substitution effect}} \Bigg) \tag{2.7}$$

Adopting more digital inputs as a share of total inputs thus has two effects on marginal emissions:

1. **Efficiency Gains Effect** If $\frac{\partial \Delta(d_i)}{\partial d_i} < 0$, then emissions decrease as a result of shifting the input bundle composition towards digital. On the other hand, if $\frac{\partial \Delta(d_i)}{\partial d_i} \geq 0$, digital adoption has either no efficiency improvements or potentially *increases* emissions. The actual effect will depend on the evolving state of technology and on how digital inputs are used.

2. **Substitution Effect** The second term of equation (2.7) refers to the effect of firms switching from non-digital to digital inputs, holding total inputs constant, X_i. If $\tilde{\phi}_D < \tilde{\phi}_N$, and digital inputs are directly cleaner and/or digitalization results in using cleaner inputs upstream, then this will decrease total emissions on the margin.

Much of the expected positive impact of digital input adoption on emissions rests on key assumptions ensuring that the two aforementioned effects are going in the right direction: $\frac{\partial \Delta(d_i)}{\partial d_i} < 0$ and that $\tilde{\phi}_D < \tilde{\phi}_N$. If these inequalities do not hold, then it is possible for emissions to increase as a result of greater digital input adoption. For example, it could be that $\frac{\partial \Delta(d_i)}{\partial d_i} > 0$ if digital inputs do not technologically improve the efficiency of production. Moreover, albeit less likely, it is not implausible that $\tilde{\phi}_D \geq \tilde{\phi}_N$ if digital inputs have a high physical footprint for specific digital goods (e.g. computers made from other dirty inputs). It could even be the case that, in a given sector, one effect offsets the other. The impact of digitalization on emissions per unit of input thus depends both on how "green" they are and on how effectively those inputs are used.

Emissions Intensity We can define emissions intensity as emissions per unit of output:

$$\frac{E_i}{Y_i} = \frac{\Delta(d_i)\left[\tilde{\phi}_N + (\tilde{\phi}_D - \tilde{\phi}_N)d_i\right]}{A_i\left[\gamma d_i^{\xi} + (1-\gamma)(1-d_i)^{\xi}\right]^{1/\xi}} \tag{2.8}$$

Taking logs of equation (2.8), and taking the derivative with respect to the log of d_i:

$$\frac{\partial}{\partial \ln d_i} \ln\left(\frac{E_i}{Y_i}\right) = \underbrace{d_i\left(\frac{\partial \Delta(d_i)}{\partial d_i}\frac{1}{\Delta(d_i)} + \frac{\tilde{\phi}_D - \tilde{\phi}_N}{\tilde{\phi}_N + (\tilde{\phi}_D - \tilde{\phi}_N)d_i}\right)}_{=\frac{\partial \ln E_i}{\partial \ln d_i}} - \underbrace{\frac{\gamma d_i^{\xi} - d_i(1-\gamma)(1-d_i)^{\xi-1}}{\gamma d_i^{\xi} + (1-\gamma)(1-d_i)^{\xi}}}_{=\frac{\partial \ln Y_i}{\partial \ln d_i}} \tag{2.9}$$

Now we have a clear picture as to how digital input adoption affects emissions intensity depending on the sign and magnitude of the emission and output elasticities. Similar to Lange et al. (2020), we can define two key effects:

1. **Rebound Effect** The classic rebound effect occurs if $\frac{\partial \ln Y_i}{\partial d_i} > 0$, so that making the production process more efficient via digitalization leads to an increase in final demand.

2. **Decoupling Effect** Decoupling occurs whenever $\frac{\partial \ln Y_i}{\partial d_i} > \frac{\partial \ln E_i}{\partial d_i}$, so emissions grow less quickly than output and emission intensity is decreasing. *Absolute decoupling* requires the

more stringent condition $\frac{\partial \ln Y_i}{\partial d_i} > 0 > \frac{\partial \ln E_i}{\partial d_i}$. In this case, firms are able to increase output at the same time as decreasing emissions. This is the oft-cited claim on what digitalization can do for the environment. *Relative decoupling*, which corresponds to the situation where $\frac{\partial \ln Y_i}{\partial d_i} > \frac{\partial \ln E_i}{\partial d_i} > 0$ is a less favorable case, but still implies some efficiency gains.

Rearranging equation (2.9) allows us to express the effect on total emissions as the composition of the effects on output multiplied by the one on intensity:

$$\frac{\partial \ln E_i}{\partial \ln d_i} = \underbrace{\frac{\partial}{\partial \ln d_i} \ln \left(\frac{E_i}{Y_i} \right)}_{\text{intensity effect}} + \underbrace{\frac{\partial \ln Y_i}{\partial \ln d_i}}_{\text{output effect}} \tag{2.10}$$

Ultimately, we can outline the necessary conditions for absolute emissions to decline as a result of the adoption of digital inputs. Consider first the case in which emission intensity is increasing, meaning that digital is actually on net a "dirty" input. This could be the result of digital inputs having a higher physical footprint ($\tilde{\phi}_D > \tilde{\phi}_N$), or of digital adoption yielding an increased emissions multiplier, for example as a result of requiring more energy.[10] In this case, total emissions would only decrease if output itself decreases enough to more than compensate the negative intensity effect. As sectors with higher rates of technology adoption tend to grow faster than the average sector in the economy, this case seems unlikely, so increasing emission intensity as a result of digitalization is probably unambiguously bad news.

Consider now the case in which emissions intensity decreases. Then, for total emissions to decrease, it must be the case that either output decreases or does not increase fast enough to more than compensate these efficiency gains. Formally, this is the case if $\frac{\partial \ln Y_i}{\partial \ln d_i} < \left| \frac{\partial}{\partial \ln d_i} \ln \left(\frac{E_i}{Y_i} \right) \right|$. This is an important result, which corresponds to the relative decoupling case: even if the econometric model estimates an improvement in emission intensity, this may not imply absolute emission gains.

Linking to the Data The model can be directly related to the three sets of specifications we will run. Consider the following regressions, the first two for the impact of digital input shares on emissions and output in levels respectively, and the third one with emissions per unit of output as the outcome:

$$\ln(E_i) = \alpha^E + \beta^E \ln d_i + \eta^E \mathbf{X}_i' + \varepsilon_i^E \tag{2.11}$$

$$\ln(Y_i) = \alpha^Y + \beta^Y \ln d_i + \eta^Y \mathbf{X}_i' + \varepsilon_i^Y \tag{2.12}$$

$$\ln \left(\frac{E_i}{Y_i} \right) = \alpha^I + \beta^I \ln d_i + \eta^I \mathbf{X}_i' + \varepsilon_i^I \tag{2.13}$$

where $\mathbf{X}_i'$ is a vector of observable covariates. These three sets of estimates provide a decomposition of the impact of digitalization on emissions in terms of efficiency gains and output effects.

[10] It would be sufficient for one effect to offset the other, for example if the substitution effect towards dirtier digital inputs offsets any efficiency gains in the use of such technology.

We can combine equations (2.11), (2.12), and (2.13):

$$\begin{aligned}\ln(E_i) &= \ln\left(\frac{E_i}{Y_i}\right) + \ln(Y_i) \\ &= \underbrace{(\alpha^I + \alpha^Y)}_{=\alpha^E} + \underbrace{(\beta^I + \beta^Y)}_{=\beta^E} \ln d_i + \underbrace{(\eta^I + \eta^Y)}_{=\eta^E} \mathbf{X}_i' + + \underbrace{(\varepsilon_i^I + \varepsilon_i^Y)}_{=\varepsilon_i^E}\end{aligned}$$

β^E nicely recovers the core result from equation (2.10) regarding the effect of digital adoption on emissions levels, reflecting the combination of the marginal impact on emissions intensity and on output, and therefore provides a clean way to interpret the results. As discussed above, of specific interest are the sign of the intensity effect, β^I, which indicates whether there are efficiency gains, and its magnitude relative to the output effect, β^Y.

3 Data and Empirical Strategy

3.1 Data

3.1.1 Greenhouse Gas Emissions

Downstream Sector-Level Emissions We use the OECD's Greenhouse Gas Footprints (GHGFP) data to measure emissions in downstream sectors. This is available across 76 countries and 45 sectors from 1995 to 2019. We primarily focus on emissions resulting from production-based activities to better isolate the component of emissions driven by domestic downstream sectors.

Emissions by Scope Digitalization may reduce emissions by increasing production efficiency and reducing coordination costs, but it may also shift or increase emissions through greater electricity use or reliance on carbon-intensive digital infrastructure and/or upstream inputs. To further unpack sector-level emissions, we thus also gather data on emissions by "scope" following the Greenhouse Gas Protocol. This provides a sense of whether emissions within sectors increase as a result of downstream or upstream activities.

Scope 1 refers to direct emissions from sources owned or controlled by a firm, such as on-site fuel combustion or emissions from company-owned vehicles. Scope 2 includes indirect emissions from the generation of purchased energy, primarily electricity. This is particularly relevant for digitally intensive firms that rely heavily on electricity to power data centers, servers, and other IT infrastructure. Scope 3 encompasses all other indirect emissions that occur across a firm's value chain, such as emissions from upstream sectors (e.g. those associated with the production and transportation of purchased goods and services).

3.1.2 Input-Output Tables

Digital Inputs We use the OECD's inter-country input-output (ICIO) tables to gauge the input content of downstream sectors both from domestic upstream industries and from upstream suppliers among trading partners. We match this to the GHGFP data, and so similarly have coverage across 76 countries in 45 sectors between 1995-2019. We are thus able to gauge, for example, how much American telecommunications' input are sourced from itself, from telecommunications from other countries, and from all other sectors besides telecommunications domestically and from other countries, over time.

To identify digital inputs, we define the digital sector as comprising: 'Computer, electronic and optical equipment', 'Telecommunications' and 'IT and other information services'. While this is understandably a crude approach, it is consistent with other contributions using the OECD's ICIO data (e.g. Nose and Honda, 2023), and largely captures the general consensus as to what defines digitalization (e.g. Calvino et al., 2018). It is also able to broadly cover both "hard" and "soft" components of the digital sector, from, say, physical semiconductors to software-related services.

Total Output From the ICIO tables, we also collect information on total output across downstream sectors within countries. Dividing total emissions by total output allows us to measure the intensity of emissions per unit of gross production, as per our model in section 2. This represents how carbon-efficient the production process is at the gross production level.

3.2 Stylized Facts

Before we empirically assess the impact of digital inputs on emissions in downstream sectors, we provide a set of stylized facts below on the size and centrality of digital inputs in global supply chains. Although Figure 1 suggests that on average digital inputs have increased in absolute levels over time across country-sectors, this does not precisely convey whether the digital sector has become more important or "central" in production across the planet. A standard measure from the production networks literature is hence the first-order "weighted outdegree" of a given sector (Acemoglu et al., 2012).

Following the model in section 2, once firms choose optimal digital and non-digital inputs subject to prices and elasticities, this gives rise to an $S \times S$ equilibrium input-output matrix, $\mathbf{W}$, with row i and column j representing upstream and downstream sectors, respectively. Elements $x_{ij} \in \mathbb{R}_+$ represent the amount of input from sector i (upstream) that sector j (downstream) uses for its own production of goods and services. Normalizing x_{ij} by the total inputs that sector j uses for production, we obtain a measure $w_{ij} = x_{ij} / \sum_{i=1}^{S} x_{ij}$ that gauges the share of inputs sector s uses from sector i. Hence, if $w_{ij} = 1$, then sector j's output is driven solely by the output from upstream sector i as an intermediate input.

The first-order "weighted outdegree" tells us how important an upstream sector i is to all S downstream sectors (both domestically and internationally in the context of inter-country input-output data). When applied to the digital sector, this amounts to performing a row sum across downstream use sectors:

$$D_i = \sum_{j=1}^{S} d_{ij} \in [0, S], \text{ where } d_{ij} = \frac{\sum_{j \in \mathcal{D}} x_{ij}}{\sum_{i=1}^{S} x_{ij}} \tag{3.1}$$

Here, d_{ij} directly connects to equation (2.3) from our model, i.e. the share of inputs that come from the digital sector. Using the OECD ICIO data, we calculate this for the digital sector and average across all countries over time, although note the empirical analog is calculated from total sales versus pure quantities (which is unavailable in the data). This is shown in panel (a) of Figure 2, which yields our first stylized fact.

Fact 1: the digital sector has become highly central in global supply chains over time.

This first stylized fact may seem somewhat unsurprising in light of the 'Information Age'. However, it is worth noting the difference in trends between panel (a) of Figure 2 and the series in Figure 1: while total digital inputs have increased monotonically over time, the centrality of the digital sector has not increased as linearly.

(a) Global **(b)** Country-Level Distribution

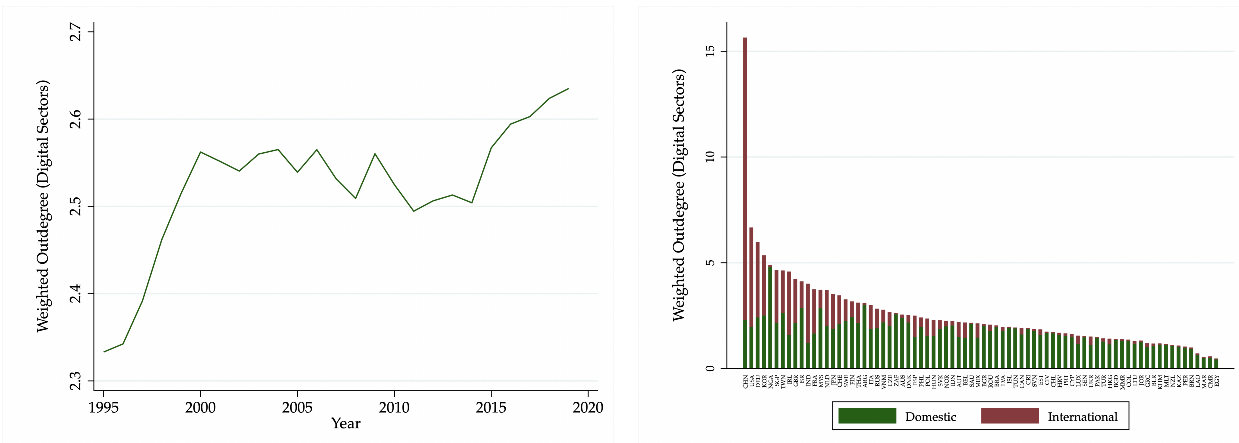
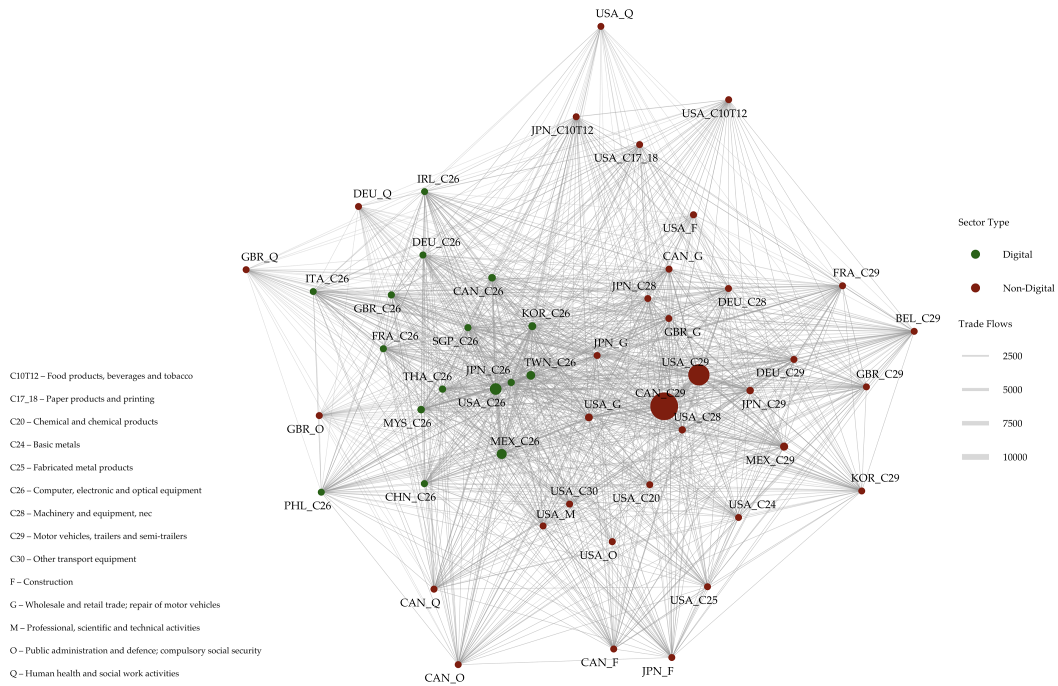


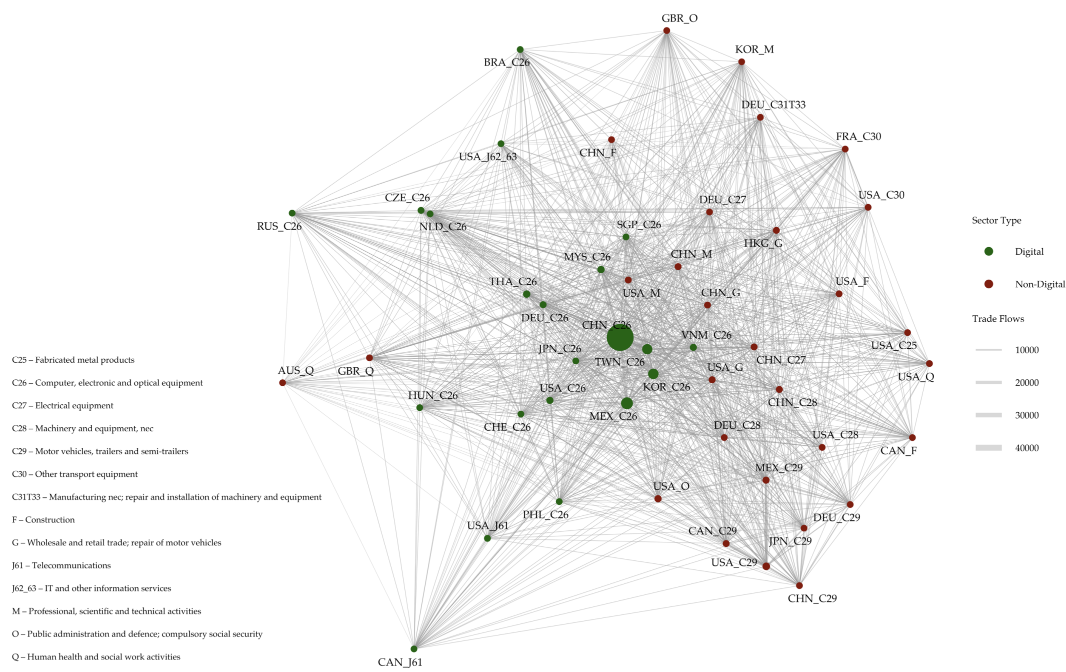
Figure 2: Weighted Outdegree of the Digital Sector

Note: the left-hand panel plots averages across countries and sectors by year. The right-hand panel plots averages between 2010-2019. 'Domestic' refers to calculating the weighted outdegree of domestic digital upstream sectors to domestic downstream sectors. 'International' refers to calculating the weighted outdegree of domestic digital upstream sectors to downstream sectors among trading partners.

Given we use ICIO tables, we can unpack panel (a) of Figure 2 with respect to both the centrality of countries as trading partners of intermediate digital inputs across global supply chains in addition to the centrality of domestic upstream suppliers. Regarding the former, this amounts to calculating the weighted outdegree in equation (3.1) but never including domestic downstream sectors (e.g. assessing France's importance as a digital supplier across all trading partners' downstream sectors). Panel (b) of Figure 2 shows China as the dominant global supplier of digital inputs, followed by the United States, Germany, and South Korea.



(a) Top 50 Most Central Country-Sectors (1995)



(b) Top 50 Most Central Country-Sectors (2019)

Figure 3: Most Central Country-Sectors in Global Production Networks (1995 and 2019)

Note: nodes weighted by eigenvector centrality. Only top 50 nodes of entire graph per year are plotted. Edges refer to trade flows in million USD.

As an alternative metric of centrality, we further calculate the eigenvector centrality of country-sectors in global supply chains, comparing this between 1995 and 2019 (a long difference between the earliest and latest year of our analysis). This calculates how strongly a given sector is connected to other highly connected sectors in the global production network, thereby capturing systemic importance rather than the size of first-degree linkages. As shown in Figure 3, while North American manufacturing dominated supply chains in the 1990s, today this has shifted substantially towards the digital sector, with Chinese 'computer, electronic and optical equipment' being the most central sector over two decades later.

Fact 2: digital input intensity is largest in digital and services sectors, and lowest in manual- and resource-intensive sectors.

As a second stylized fact in the data, we now calculate across sectors globally what is their average digital input reliance as a share of total inputs. As per panel (a) of Figure 4, we clearly see that the digital sector itself uses a large share of digital inputs, with approximately a third of inputs in the digital sector being sourced from itself. In non-digital sectors, services such as publishing, audiovisual and broadcasting activities ('Publishing & Media'), professional, scientific and technical activities ('Professional Services') and finance and insurance ('Financial and insurance activities') are the second group of sectors that rely heavily on digital inputs.

(a) Digital Input Intensity **(b)** Production-Based Emissions

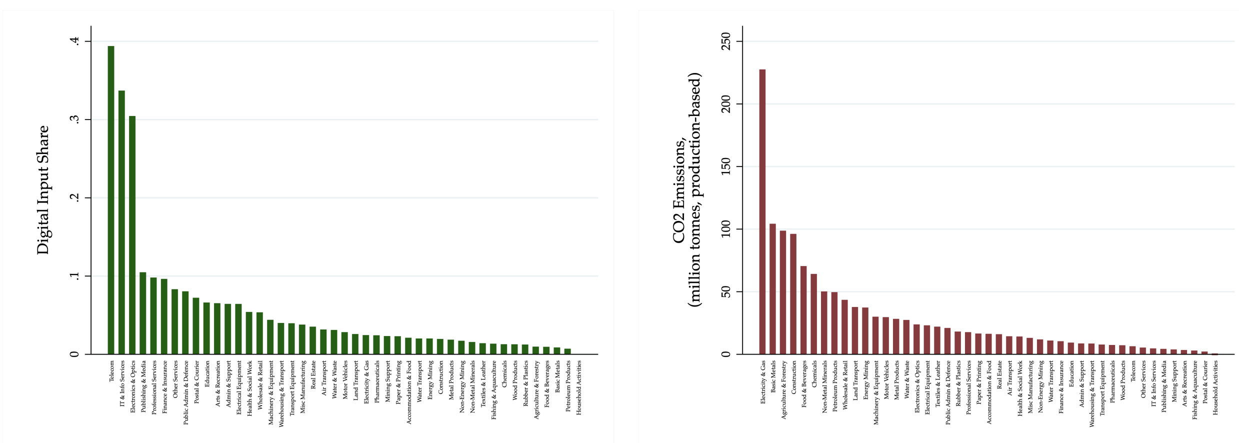


Figure 4: Digital Input Intensity and Emissions by Sector

Note: data plots averages across countries between 2010-2020. Digital input share outlines the proportion of a downstream sectors' inputs from the digital sector relative to total inputs. Sector names have been abbreviated from the International Standard Industrial Classification (ISIC, Rev. 4) used by the OECD.

At the other end of the distribution, manual- and resource-intensive industries such as agriculture, hunting, forestry ('Agriculture & Forestry'), food products, beverages and tobacco ('Food & Beverages'), basic metals ('Basic Metals') and coke and refined petroleum products ('Petroleum Products') have more limited uses of digital inputs relative to total inputs. Hard-to-abate sectors, where it is argued digital has the most potential for emissions reductions (World Economic Forum, 2022), also have fairly middling levels of digital input adoption, from the transport sector (e.g. 'Air Transport') to energy (e.g. 'Electricity & Gas') and heavy industry (e.g. 'Construction').

Fact 3: hard-to-abate sectors – energy, heavy industry, and transport – drive the majority of global emissions.

Finally, to a get a sense of which industries are the most polluting in the data, panel (b) of Figure 4 outlines total CO2 emissions from production-based activities across sectors. Clearly, hard-to-abate sectors such as energy, heavy industry, and transport are the most energy-intensive. On the other hand, the digital sector and services are far less polluting. This leads to our third stylized fact.

This is not necessarily a new finding. Nonetheless, in comparing to panel (a) of Figure 4, there is clearly somewhat of a descriptive inverse relationship: the most energy-intensive sectors are the least likely to use digital inputs as a share of total inputs. Although both panels of Figure 4 average across countries and over time, the inverse relationship between the two charts points to the idea that relative digital input adoption may potentially contribute to reductions in greenhouse gas emissions. While the material outputs of sectors are extremely diverse, perhaps digital and service sectors are least polluting precisely because of their digital input content, but it could also be that digital inputs are less relevant to more polluting sectors. This is what we set out to empirically test.

3.3 Empirical Strategy

3.3.1 Static Fixed Effects

The increased digitalization of the economy that has occurred worldwide since the 1990s provides a natural testing ground to explore the ideas in this paper. Our identifying variation exploits the fact that, following this trend, different sectors within countries adopt digital inputs at different intensities at distinct times. This provides meaningful variation to exploit within-country-sector variation of digital input adoption vis-á-vis greenhouse gas emissions. We run the following specification:

$$\ln(g_{c,s,t}) = \alpha_{c,t} + \gamma_{c,s} + \delta_{s,t} + \beta \ln(d_{c,s,t}) + \eta \mathbf{X'}_{c,s,t} + \varepsilon_{c,s,t}, \tag{3.2}$$

Here, $g_{c,s,t}$ refers to GHG emissions in country c of downstream sector s in year t. As mentioned above, we decompose the impact on total emissions by also estimating the effect of digital adoption on emissions as a share of total output (the intensity of emissions), and on total output, $y_{c,s,t}$, to evaluate rebound effects.

Our core regressor, $d_{c,s,t} = x^{\text{digital}}_{c,s,t} / \sum x_{c,s,t}$, measures digital inputs as a share of total inputs. This helps capture the "intensity" of digital inputs in the overall supply chains of downstream sectors, and naturally connects to the derived optimal input share from our theoretical model in equation

(2.3). Again, similar to the calculation of the weighted outdegree in equation (3.1), our empirical analog relies on total sales as opposed to quantity shares given the ICIO OECD data. $\mathbf{X}'_{c,s,t}$ refers to a vector of observable covariates, and $\varepsilon_{c,s,t}$ refers to an idiosyncratic error term. Given the level of treatment variation occurs at the country-sector level, we cluster standards error by country-sector.

For our core analysis, we use a rich set of interactive fixed effects which includes country-sector, $\gamma_{c,s}$, country-year, $\alpha_{c,t}$, and sector-year, $\delta_{s,t}$, fixed effects. This absorbs any time-invariant characteristics at the country-sector level, in addition to all time varying observables and unobservables at the country and sector level, respectively. This could include unobserved factors such as shocks from national policies, in addition to addressing any trends within sectors, such as sectors simply becoming technologically more advanced over time. Albeit a demanding and saturated specification, this purely exploits within-country-sector variation, and thus allows us to more directly answer whether, as a specific country-sector adopts digital inputs as a greater share of total inputs, this impacts emissions and output. To understand the potential nature and direction of bias, in some specifications we also include a plain vanilla additive fixed effects structure of country, sector and year dummies, for comparison.

4 Global Results

4.1 Static Fixed Effects Results

Table 1 outlines the results using our core specification, where we include fixed effects both additively and interactively for comparison. In column 1, using an additive fixed effects structure, we find evidence that digital adoption as a share of total inputs is negatively associated with total emissions. Albeit only significant at the 10% level, this is the widely discussed result in policy circles, that digitalization can decrease emissions.

Nonetheless, as per column 2, once fully exploiting within-country-downstream sector variation with a fully saturated interactive fixed effects model, the relationship between digital inputs and emissions attenuates to zero. This suggests in cross-sectional comparisons, those sectors on a steeper emissions trajectory may concurrently be investing more in digital, thus leading to an upward biased effect in column 1.

Against intuition, in both columns 3 and 4 we find some statistically significant evidence that digital adoption decreases total output. Using preferred specification in column 4, we find that a 10 percent increase in digital input adoption as a share of total inputs *decreases* output by 0.19 percent. This would suggest in economic terms that, *ceteris paribus*, digitalization does not increase total production volume.

Finally, columns 5 and 6 explore the impact on emissions per unit of output to explore potential efficiency gains from digitalization. In column 6, using the interactive fixed effects approach, we find that digital input adoption as a share of total inputs increases emissions per unit of output, significant to the 5% level. Following the model in section 2, this mechanically results from decreases in emissions and output concurrently, taking the difference in estimates between columns 2 and 4.

Overall, evidence for the virtuous environmental impacts of digitalization is not apparent from the results in Table 1. To reiterate, columns 2, 4 and 6 of Table 1 use highly saturated specifications that includes country-sector, country-year and sector-year fixed effects. This absorbs several sources of underlying variation that could concurrently drive input adoption, emissions and sectoral performance. As such, although the results in Table 1 are purely suggestive, null effects are unlikely to be driven by potential policy-driven or technology-related unobservables.

Table 1: Static Fixed Effects Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Emissions		**Total Output**		**Emissions per Unit of Output**	
Digital Input Share	-0.041*	-0.002	-0.043*	-0.019**	-0.001	0.018**
	(0.025)	(0.010)	(0.025)	(0.008)	(0.012)	(0.008)
Observations	82,968	82,968	83,220	83,220	82,968	82,968
Country FE	Yes	No	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Country × Sector FE	No	Yes	No	Yes	No	Yes
Country × Year FE	No	Yes	No	Yes	No	Yes
Sector × Year FE	No	Yes	No	Yes	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by country-sector in parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed. Emissions per unit of output is total emissions divided by total output.

4.2 Emissions by Scope

In this section, we unpack the origin of emissions by "scope" following the Greenhouse Gas Protocol. This exercise allows us to better capture how digital input adoption in one sector influences emissions outcomes across upstream and downstream activities. Table 2 provides results estimating equation (3.2) using each emissions scope as the outcome variable. Using our preferred specifications in panel B, measuring emissions in both absolute levels and relative to units of output, we find null effects for scope 1 emissions. This suggests digitalization has led to no consequential change in direct on-site emissions of firms.

In column 2, we find consistent results for *increases* in scope 2 emissions, which also holds in column 5 when normalizing by total outputs. This result appears irrespective of using an additive or interactive fixed effects specification, although results in panel B are larger in magnitude. Hence, digitalization not only augments scope 2 emissions in absolute levels, but does not yield any efficiency gains when measuring emissions relative to gross output. Using the estimates from panel B, the elasticity suggests a 10 percent increase in digital input share is associated with a 2.4 to 2.7 percent increase in scope 2 emissions and emissions per unit of output, respectively. This suggests that adoption of greater digital inputs as a share of total inputs requires greater energy consumption, primarily electricity, for production in downstream sectors. Such a result is highly plausible, and is especially relevant for digitally intensive sectors that may rely heavily on, say, data centers and IT infrastructure. Although note that this effect could be muted in countries that use cleaner energy grids (e.g. France) rather than from countries with coal-heavy power grids (e.g. India).

Finally, in column 3, there is some evidence of a decrease in absolute levels of scope 3 emissions. However, in panel B, this decrease is clearly offset by estimated decreases in total output when estimating the intensity of scope 3 emissions in column 6. There is consequently further limited evidence that digital inputs are driving efficiency gains via cleaner inputs for production from upstream or downstream sources.

Table 2: Static Fixed Effects Results by Emissions Scope

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Additive Fixed Effects	**Scope 1 (Levels)**	**Scope 2 (Levels)**	**Scope 3 (Levels)**	**Scope 1 (per Unit of Output)**	**Scope 2 (per Unit of Output)**	**Scope 3 (per Unit of Output)**
Digital Input Share	-0.085***	0.140***	-0.058***	-0.003	0.241***	-0.017**
	(0.029)	(0.025)	(0.025)	(0.025)	(0.024)	(0.008)
Panel B - Interactive Fixed Effects						
Digital Input Share	0.009	0.243***	-0.021**	0.028	0.268***	-0.001
	(0.019)	(0.021)	(0.010)	(0.020)	(0.022)	(0.007)
Observations	80,997	79,656	82,915	80,997	79,656	82,915

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by country-sector in parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed. Emissions per unit of output is total emissions divided by total output. Scope 3 refers to scope 3 emissions from upstream and downstream sources. Panel A uses country, sector and year fixed effects additively. Panel B uses country $\times$ sector fixed effects, country $\times$ year fixed effects and sector $\times$ year fixed effects.

4.3 Robustness Checks

Lagged Effects Although we estimate the contemporaneous effect of digitalization on emissions and sectoral performance in equation (3.2), adoption of productivity-enhancing technologies as input may have delayed impacts in realizing efficiency gains. In Appendix B.1, we thus try a lagged structure for digital input share by one year and five years. This also helps to isolate pre-treatment variation in input composition, and to avoid potential simultaneity between emissions and input choices (i.e. if the input mix and emissions are jointly determined by considerations over output levels).

Dropping Units To ensure the core results in Table 1 above are not driven by the presence of any outliers, we pursue a type of jackknife procedure where we sequentially drop countries and sectors. Our core null effects remain largely stable. See Appendix B.2.

Dynamic Effects The results in Tables 1 and 2 focus on static treatment effects. Although $d_{c,s,t}$ in equation (3.2) is a continuous measure, we are naturally assuming there are "parallel trends" in emissions and output between country-sectors that adopt more or less digital inputs as a share of total inputs over time. In Appendix B.3, we pursue this more directly via an event study, defining the treatment variable for extensive margin variation based on whether a country-sector adopted more digital inputs as a share of total inputs greater than the 90th percentile of the distribution within sectors (Aghion et al., 2023). We continue to find similar null effects, and largely confirm the lack of pre-trends in digital adoption.

5 Shift-Share Instrumental Variables Strategy

Whether firms within industries adopt more digital inputs into their supply chains is clearly an endogenous decision. Emission levels in downstream sectors may influence firms' subsequent adoption of digital inputs upstream, as industry leaders and policymakers may increasingly embrace digital solutions to reduce emissions. Although our results in Table 1 rely on an interactive fixed effects approach to agnostically absorb time-varying unobservables at the country and sector level, alongside time-invariant unobservables at the country-sector level, there may still be other characteristics that co-determine digital input adoption and relevant outcomes. In this section, we thus develop a basic shift-share instrument to predict input diffusion (Borusyak et al., 2022).

5.1 The Share: Initial Input-Output Linkages

The endogenous production networks literature has provided core theoretical insights into the forces that drive input adoption (Oberfield, 2018; Acemoglu and Azar, 2020). As motivated by Carvalho and Voigtländer (2015), input diffusion typically follows a preferential attachment model, such that pre-existing input-output linkages are used in the search for new inputs; inputs from one sector are more likely to be adopted from another sector if these two sectors are "closer" at the outset.[11] This consequently suggests that initial input-output linkages between downstream sectors and upstream sectors, both domestic and foreign, can provide some predictive power over whether inputs are eventually adopted via increased trade. As shown in Appendix D.1, sectors with higher initial digital input intensity at baseline in 1995 indeed accumulate these inputs faster

[11] This is inspired by the logic of social network formation from Jackson and Rogers (2007), whereby friends are more likely to be friends if there is a mutual friend (i.e. node) that connects them.

in subsequent years, and this pattern holds across both digital and non-digital sectors.

Following Acemoglu et al. (2016a), we thus rely on the Leontief inverse, as defined in equation (2.4) in section 2, to fully capture all input-output linkages, both direct and indirect. Empirically, using the ICIO data, we take 1995 as the base year so that input shares are pre-determined, $\mathbf{\Omega}^{1995} = (\mathbf{I} - \mathbf{A}^{1995})^{-1}$, where $\mathbf{A}^{1995}$ is the respective technical coefficients matrix. This allows us to construct measures of sectoral exposure to foreign technological shocks that are not mechanically driven by contemporaneous trade patterns. In particular, shocks originating in one country–sector propagate through the network via the Leontief structure, generating differential exposure to the shock across other country–sector pairs.

5.2 The Shifter: the China (Digital) Shock

Much of the shift-share literature has been motivated by the "China shock", such that domestic industries (especially in the United States) have been impacted by exports from China following its entry into the WTO in 2001 (Autor et al., 2013a, 2016). Given much of China's growth and eventual comparative advantage emerged following domestic economic policies, it is argued this provides some quasi-exogenous source of variation in the inputs and outputs of downstream industries among trading partners.

Although much of this literature has focused on manufactured goods broadly construed, a large component of these products involve the digital sector. Following our stylized facts, this is explicitly conveyed by Figure 3, which shows not only the growth in Chinese digital inputs relative to 1995, but also that China's digital sector, namely 'computer, electronics and optical equipment', has become the *most central* sector in global supply chains in recent years. This is consistent with Panel (b) of Figure 2 which shows that China's digital sector's weighted outdegree among foreign trading partners is clearly a large outlier in the global distribution.

We label this finding the "China digital shock", and exploit China's rise as a focal digital exporter to provide quasi-exogenous variation in the supply of digital inputs globally. Following a standard approach in this literature, to isolate the exogenous component of the shock, we use growth in total Chinese digital imports in the same sector among all non-regional economies:

$$\ln \Delta(D_{c',s,t}) = \ln \Delta \left(\text{Digital Imports from China}_{c',s,t} \right), \tag{5.1}$$

Here, c' refers to the set of countries in all other regions beyond country c (e.g. for Germany we would use total digital imports from China across all economies outside of Europe).[12] This helps to ensure the diffusion of digital inputs from China are not driven by direct bilateral trade dynamics, but instead reflect broad, plausibly exogenous changes in China's global digital export supply.

[12] We use the World Bank's region classifications: East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia and Sub-Saharan Africa.

5.3 Specification

Using the Leontief inverse from the 1995 ICIO matrix from our OECD data, $\mathbf{\Omega}^{1995}$, we follow Acemoglu et al. (2016a,b) by constructing downstream and upstream versions of the China digital shock:

$$Z^{\text{down}}_{c,s,t} = \sum_{c'}\sum_{s'}\left(\Omega^{1995}_{(c',s'),(c,s)} - \mathbf{1}_{(c',s')=(c,s)}\right)\cdot\Delta\ln\left(D_{c',s',t}\right), \tag{5.2}$$

$$Z^{\text{up}}_{c,s,t} = \sum_{c'}\sum_{s'}\left(\Omega^{1995}_{(c,s),(c',s')} - \mathbf{1}_{(c',s')=(c,s)}\right)\cdot\Delta\ln\left(D_{c',s',t}\right), \tag{5.3}$$

where $\mathbf{1}_{(c',s')=(c,s)}$ is an indicator equal to one if (c', s') corresponds to the same country-sector (c, s), ensuring that the direct own-sector shock is not included.[13]

The Leontief inverse thus allows us to capture the impact of shocks working in two directions via input-output linkages. On the one hand, the shock may be "downstream" such that suppliers to country-sector (c, s) digitalize from China, which then propagates to the country-sector itself. On the other hand, the shock may be "upstream" such that customers of a given country-sector directly digitalize their input content from China, thereby affecting demand for digitally intensive intermediates produced by (c, s). Our corresponding first-stage specification is thus:

$$\ln\left(d_{c,s,t}\right) = \alpha_{c,t} + \gamma_{c,s} + \delta_{s,t} + \xi^{\text{down}} Z^{\text{down}}_{c,s,t-1} + \xi^{\text{up}} Z^{\text{up}}_{c,s,t-1} + \eta\mathbf{X'}_{c,s,t-1} + u_{c,s,t-1} \tag{5.4}$$

We continue to include country-sector, country-year, and sector-year fixed effects to identify within-country-sector variation net of time-varying country- and sector-level unobservables.[14] We lag the instrument by one year to isolate the pre-treatment impact of foreign productivity shocks on the intensity of digital input adoption. For ease of interpretation, we also standardize $Z^{\{\text{down,up}\}}$ to interpret the first stage in terms of standard deviation increases of the shocks on digital adoption.

Identification rests on the standard relevance assumption, such that $\text{Cov}(d_{c,s,t}, Z^{\{\text{down,up}\}}_{c,s,t-1}) \neq 0$, and the exclusion restriction, $\mathbb{E}[Z^{\{\text{down,up}\}}_{c,s,t-1}\varepsilon_{c,s,t}] = 0$, such that productivity shocks in digital sectors among trading partners only impact emissions and sectoral performance through digital input adoption. Albeit an untestable assumption, our rich set of fixed effects arguably absorbs several sources of underlying variation that might drive demand shocks within country-sectors that correlate with the digital supply expansion from China.

[13] Omitting the own-sector shock helps further isolate the supply-side, exogenous component of China's rise as a digital exporter, given demand-side factors could lead to direct bilateral ties between a given country-sector and China's digital expansion.

[14] The inclusion of a country-sector fixed effect allays the issue that our share does not mechanically sum to one (i.e. "incomplete shares") (Borusyak et al., 2025). We rely on the "exogenous shifts" approach to identification, such that shifts are assumed to be as-good-as-randomly assigned as a share-weighted average.

5.4 Shift-Share IV Results

5.4.1 Core Results

Table 3 illustrates the results using our China digital shock instrument. In contrast to the results in Table 1, panel A for our second stage results shows that we now find an overall *increase* in total emissions following digitalization. As per column 1, a 10 percent increase in digital input adoption as a share of total inputs increase total emissions from production in domestic downstream sectors by 8 percent. In column 2 for output, we find that a 10 percent increase in digital input share increases total output in domestic downstream sectors by 2.5 percent, although this is a far noisier estimate. In column 3, a 10 percent increase in digital input adoption increases emissions per unit of output by 4.9 percent.

The positively-signed results in columns 1 and 2 versus the negative estimates in Table 1 suggest our previous results have a strong downward bias. Again, this could be reflective of sectors on a steeper efficiency improvement trajectory adopting digital inputs faster (Aklilu et al., 2024; Calvino et al., 2024). Moreover, it is clear from our F-test statistics, which we calculate following Olea and Pflueger (2013) ('effective" F-test), that our China digital shock instruments are somewhat weak. This is not too surprising; the usual China shock literature exploits only variation within a specific national context (usually the US), as opposed to evaluating the impact of the shock globally (Autor et al., 2013b, 2016). The fact that we use all non-regional economies to isolate the exogenous component of the shock also likely contributes to a weaker instrument, albeit necessary for cleaner identification. For this reason, we provide Anderson-Rubin confidence intervals which are robust to weak instruments, where at least for columns 1 and 3 the uncertainty estimates are bounded. Moreover, our Anderson-Rubin F-tests reject the null hypothesis of no effect of digital input adoption on emissions. This implies that our results remain statistically identified and robust even under weak-instrument conditions (Andrews et al., 2019; Keane and Neal, 2024).

When looking at the first stage in panel B, we find an interesting pattern such that the impact of the China digital shock increases digital input adoption from downstream sources versus upstream impacts. If suppliers are impacted by China's digital growth in global supply chains, then this would trickle down into the inputs of downstream sectors. On the other hand, when a given country-sector's customers are impacted more heavily by the shock, this is associated with a decrease in digitalization of inputs. Although the upstream impact is less intuitive, one interpretation is that sectors digitalizing directly from China may substitute away from a previous trading partner's output. This would subsequently decrease an upstream sector's final demand, with knock-on effects on incentives to invest in digital technologies if production scales down.

Finally, the reduced form results in panel C show that only the downstream shock is associated with increases in total emissions, total output and emissions per unit of output. This suggests that the second-stage 2SLS estimates in panel A are being driven by the supply-side shock following

Table 3: Shift-Share IV Results

	(1)	(2)	(3)
Panel A - Second Stage	**Total Emissions**	**Total Output**	**Emissions per Unit of Output**
Digital Input Share$_t$	0.807**	0.254	0.488**
	(0.319)	(0.189)	(0.196)
	[0.871, 3.437]	$[-\infty, \infty]$	[0.228, 2.287]
Panel B - First Stage	**Dependent variable is Digital Input Share$_t$**		
China Digital Shock (Downstream)$_{t-1}$	0.016**	0.015**	0.016**
	(0.007)	(0.007)	(0.007)
China Digital Shock (Upstream)$_{t-1}$	-0.025**	-0.024**	-0.025**
	(0.011)	(0.011)	(0.011)
Panel C - Reduced Form	**Total Emissions**	**Total Output**	**Emissions per Unit of Output**
China Digital Shock (Downstream)$_{t-1}$	0.024***	0.013***	0.011***
	(0.005)	(0.003)	(0.003)
China Digital Shock (Upstream)$_{t-1}$	0.0012	0.008	-0.007
	(0.008)	(0.006)	(0.006)
F-test (effective)	4.691	4.486	4.691
F-test (AR)	15.943	9.511	8.167
[p-value]	[0.000]	[0.000]	[0.000]
Observations	75,215	75,294	75,215
Country × Sector FE	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by country-sector in parentheses across all panels. In the second stage (panel A), Anderson-Rubin confidence intervals are also reported in square parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed. Panel A outlines results from the second stage. Panel B outlines results from the first stage. Panel C outlines reduced form results. F-test (effective) refers to the test statistic from Olea and Pflueger (2013). F-test (AR) refers to the Anderson-Rubin F-statistic.

China's digital expansion, with the demand-side shock contributing little towards identification of the effect.[15] Regarding output in column 2, this pattern is consistent with the idea that when a sector's suppliers are exposed to the China digital shock, the resulting fall in input costs and rise in input availability enable downstream sectors to scale up production.

5.4.2 Emissions by Scope

We now unpack the results by emissions scope, similar to Table 2. In columns 1-3, our 2SLS results reveal that digital input intensity significantly affects scope 2 and scope 3 emissions, but not scope 1 emissions. These results are not too disimilar to the findings in Table 1. This pattern re-affirms the potential nature of digitalization, increasing electricity use and the sourcing of alternative, energy-intensive inputs rather than altering on-site combustion processes. As a result, firms with higher digital intensity do not significantly reduce their direct emissions (scope 1), but they do shift emissions into purchased electricity (scope 2) and supply chains (scope 3).

When looking at emissions per unit of output in columns 4-6, we find similar results. In column 4, the effect of digital adoption on scope 1 emissions per unit of output is estimated as close to zero. Although we continue to find a positive association for scope 2 emissions in column 5, this also attenuates slightly and becomes statistically indistinguishable from zero. Columns 4 and 5 thus suggest the presence of a strong rebound effect due to the parallel increase in output that prevents any efficiency gains (i.e. no relative decoupling). Finally, in column 6, we continue to find significant evidence for an impact on scope 3 emissions. Here, a 10 percent increase in digital input adoption as a share of total inputs increase scope 3 emissions per unit of output by 5.5 percent. This suggests that any efficiency gains from digital adoption do not offset the additional embodied carbon in inputs employed along the supply chain.

Consistent with panel C of Table 3, the reduced form results also suggest that the impact of China's digital expansion is largely driven by effects on suppliers. Of course relying on upstream and downstream shocks on scope 3 emissions may violate the exclusion restriction. Nonetheless, the fact that the reduced form exhibits the same directional and quantitative pattern as the first stage, being stronger for supplier exposure than for customer exposure, suggests that the emissions response operates primarily through changes in digital input intensity, rather than through any direct effect of China's expansion itself (see Appendix D.2).

Ultimately, by leveraging quasi-exogenous variation in digital input intensity within downstream sectors, our instrumental variables approach isolates this shift in the emissions profile, highlighting again how digitalization transforms where, rather than whether, emissions occur.

[15] See Appendix D.2 for a formalization of the argument.

Table 4: Shift-Share IV Results for Scope

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – Second Stage	**Scope 1 (Levels)**	**Scope 2 (Levels)**	**Scope 3 (Levels)**	**Scope 1 (per Unit of Output)**	**Scope 2 (per Unit of Output)**	**Scope 3 (per Unit of Output)**
Digital Input Share$_t$	0.319	0.867*	0.883**	0.024	0.710	0.546**
	(0.330)	(0.488)	(0.345)	(0.306)	(0.445)	(0.209)
	[-0.613, 1.919]	[-0.147, 3.877]	[1.462, 3.441]	[-0.747, 0.459]	[-0.626, 3.237]	[0.512, 2.464]
F-test (effective)	5.279	4.299	4.684	5.279	4.299	4.684
F-test (AR)	0.510	2.605	22.978	2.039	1.250	18.106
[p-value]	[0.600]	[0.074]	[0.000]	[0.1302]	[0.287]	[0.000]
Panel B – Reduced Form						
China Shock (Downstream)$_{t-1}$	0.006	0.021**	0.0290***	-0.009	0.008	0.015***
	(0.007)	(0.009)	(0.004)	(0.006)	(0.009)	(0.003)
China Shock (Upstream)$_{t-1}$	-0.007	-0.007	0.003	-0.016	-0.017	0.003
	(0.012)	(0.013)	(0.007)	(0.012)	(0.013)	(0.005)
Observations	73,563	72,314	75,190	73,563	72,314	75,190
Country × Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by country-sector in parentheses across all panels. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed. Scope 3 refers to scope 3 emissions from upstream and downstream sources. Panel A provides the second stage results. Panel B outlines reduced-form results.

5.5 Robustness Checks

Dropping Units To ensure there are no specific trade partners per country-sector that are driving the overall average results, we sequentially drop countries using a type of jackknife procedure to check sensitivity. See Appendix D.3.

Omitting Trade in Services Measures of services imports are generally less reliable than those for physical goods, as they are not subject to customs clearance or tariffs and are often delivered digitally. Unlike goods, which are tracked at the border, services imports typically rely on firm-level self-reporting through enterprise surveys or financial records, making them vulnerable to misclassification, underreporting, or omission. Given our digital input definition includes 'IT and other information services', we omit trade in this sector from equation (5.1). See Appendix D.4. Our results tend to be even stronger.

6 Within-Country Evidence: The United States

Our core results in sections 4 and 5 using the OECD ICIO tables provide a global assessment of the digital-emissions nexus. Although we have so far focused on international supply chains, there is a large amount of evidence suggesting that shocks can locally propagate within domestic production networks (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). *Intra-national* trade could thus also determine supply chain activity and the decision to adopt certain inputs from regional but *domestic* upstream sectors. This could especially be the case if there are economic hubs where digital innovation occurs and hence where inputs are sourced from, such as California's Silicon Valley in the United States.[16]

In this section, we thus rely on subnational input-output (IO) tables as an alternative, more granular source of variation. While these IO tables are fairly common across countries, especially OECD countries, information on emissions at the sector level within subnational units is not as readily available. Nonetheless, we are able to gather within-country data on both input-output content and emissions at the state-level for the United States. Following recent innovations on the measurement of digitalization (see Brynjolfsson et al., 2024), we further gauge digital adoption within sectors vis-á-vis *human capital*, as opposed to physical inputs. This helps to address potential measurement debates around digital adoption.

6.1 Data and Empirical Strategy

6.1.1 Data

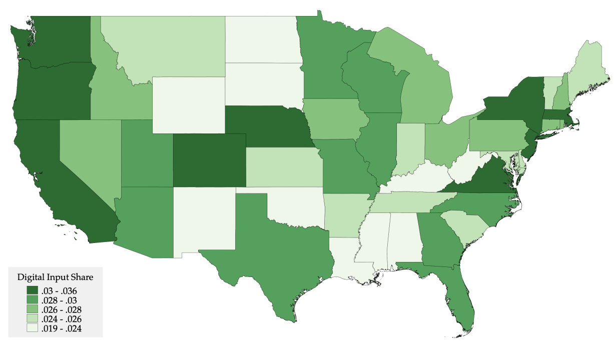
We use data from Ingwersen et al. (2022) on the 'US Environmentally-Extended Input-Output Model v2.0'. This provides IO data, alongside emissions, across all 50 states between 2012-2020

[16] In 2013, the US Department of Commerce reported in 2013 that California accounted for $68.1 billion (21 percent) of all computer and electronic products made in the United States (Diagne and Callen, 2015).

across 64 sectors (we again drop 2020 to avoid any mechanical impacts from Covid-19 and for consistency with our global results). Although we cannot appraise specific state-by-state transactions, the data allow us to separate, for each state, inputs from local upstream sectors versus a 'Rest of US' set of upstream sectors. Using this data, we define the digital sector as comprising 'Computers and relevant parts, conductors, measuring devices, communication devices', 'Data processing, internet publishing, and other information services' and 'Computer programming and systems design'. Unlike our definition from the OECD ICIO tables, Ingwersen et al. (2022) provides more granular sectors to better identify digital inputs, such as programming and systems design.

Again, to perform some quick diagnostics on the data, we outline some basic summary statistics and stylized facts. As illustrated by Figure 5, there is clear heterogeneity in digital input adoption within the context of the United States. Digitalization is thus by no means a uniform process, and suggests there is clear, meaningful variation at the state-level to exploit. Digital input intensity is largest along parts of the coasts, in addition to the heartland states of Colorado and Nebraska. States along the Northeast Corridor and the West Coast have the highest digital input shares due to their concentration of tech-driven industries, strong broadband infrastructure, and elite research institutions. The Northeast Corridor, anchored by New York, Boston, and Washington, D.C., is a hub for finance, fintech, biotech, and AI, while the West Coast, led by Silicon Valley, Seattle, and Portland, dominates in software, cloud computing, e-commerce, and semiconductors.

(a) Digital Input Intensity



(b) Production-Based Emissions

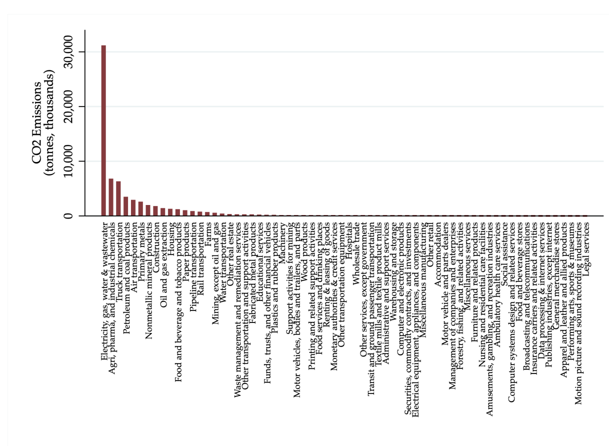


Figure 5: State-Level Variation of Digital Input Intensity and Emissions in the US

Note: averages are taken between 2012-2019. Panel (a) averages digital inputs as a share of total inputs. In panel (b), sector descriptions are abbreviations for visual clarity.

The right hand panel in Figure 5 further outlines average emissions across states broken down by sector. Sectors related to energy are always the most emission-intensive, in addition to manufacturing and transport. These trends are again concomitant with our third stylized fact in section 3.2 (despite this observation relying on global data across countries).

6.1.2 Empirical Strategy

We mimic our core specification in equation (3.2) by including state-sector fixed effects, $\alpha_{u,t}$, state-year fixed effects, $\gamma_{u,s}$, alongside sector-year fixed effects, $\delta_{s,t}$ (although we also include additive fixed effects by state, sector and year for comparability and to understand the sign and direction of potential omitted variables). We thus run the following specification, similar to equation (3.2):

$$\ln(g_{u,s,t}) = \alpha_{u,t} + \gamma_{u,s} + \delta_{s,t} + \beta \ln(d_{u,s,t}) + \eta \mathbf{X'}_{u,s,t} + \varepsilon_{u,s,t} \tag{6.1}$$

For all countries, we again measure GHG emissions, $g_{u,s,t}$, both in levels and as a share of output. Unlike the global analysis, we are limited to assessing overall production emissions and cannot unpack this by scope due to data availability from Ingwersen et al. (2022). We also use total output, $y_{u,s,t}$, as a dependent variable to gauge rebound effects. Our core regressor, $d_{u,s,t} = x^{\text{digital}}_{u,s,t} / \sum x_{u,s,t}$, continues to measure the intensity of digital inputs used in downstream production. For the idiosyncratic error term, $\varepsilon_{u,s,t}$, we cluster this at the state-sector level.

6.2 Results for the US

Table 5 outlines the results exploiting state-level variation in digital input content and emissions at the state-sector level. Similar to Table 1, we find that estimates without the inclusion of interacted fixed effects, to exploit pure within state-sector variation in digital adoption over time, are largely upward biased. In column 1, we find that digital adoption increases emissions in levels from production, although this attenuates to zero in column 2 when including state-sector, state-year and sector-year fixed effects. At least in the US context, sectors or states experiencing faster growth or greater investment in energy-intensive activities may simultaneously exhibit higher digital input shares.

Across both columns 3 and 4, we find no significant impact on total output following digitalization of inputs, although the point estimate is positive. Finally, in columns 5 and 6, we find a similar pattern to that of columns 1 and 2, such that a positive effect on emissions per unit of output is estimated under an additive fixed effects structure, although this is wiped out when using interacted fixed effects.

Overall, the lack of significant results for our core specification incorporating interacted fixed effects suggests that marginal variation in sector-level digitalization does not meaningfully correlate with either emissions or productivity in the US context. One interpretation is that the US economy, already characterized by high levels of digital penetration by 2012 (the first year of available data), may exhibit limited marginal returns, either economic or environmental, from further digitalization at the sector level. Connecting to our model in section 2, this would suggest the gradient on the efficiency multiplier, $\Delta(d_i)$, is somewhat flat.

Table 5: Results for the US

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Emissions		**Total Output**		**Emissions per Unit of Output**	
Digital Input Share	0.279***	0.023	0.005	0.010	0.277***	0.012
	(0.039)	(0.041)	(0.048)	(0.039)	(0.056)	(0.052)
Observations	26,187	26,185	26,294	26,293	26,187	26,185
State FE	Yes	No	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
State × Sector FE	No	Yes	No	Yes	No	Yes
State × Year FE	No	Yes	No	Yes	No	Yes
Sector × Year FE	No	Yes	No	Yes	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by state-sector in parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed.

6.3 Alternative Digitalization Measures

A potential critique of our approach to gauging digitalization within industries concerns focusing on measurable, hard inputs from IO tables. In the past, focusing on hard physical digital inputs, such as IT equipment, may have served as a useful proxy for digitalization within firms and industries (e.g. Bresnahan et al., 2002). However, given more recent developments, much of the modern digital transformation is arguably skill-based as a result of cloud computing, software-as-a-service (SaaS) tools, AI, and other digital platforms, and hence not driven by physical IT equipment (Biglaiser et al., 2024).

An alternative way to gauge digitalization within industries is thus to focus on *human capital*. Although there are strong complementarities between physical digital infrastructures and human capital (e.g. Brynjolfsson and Milgrom, 2013), *how* digital inputs are used matters substantially. Skilled labor, such as data analysts, software developers, and IT specialists, signals that an industry is actively integrating digital tools into its operations. Hence, human capital captures the organizational and behavioral shifts necessary for a meaningful digital transformation to occur.

To gauge digital human capital, we use the dataset developed by Brynjolfsson et al. (2024). Derived from approximately 330 million job postings at the firm-level across the United States (now at the aggregate national-level, not state-level) since 2010, this provides industry-wide indicators of digital-related human capital. This can be broken down into six-digit North American Industry Classification System (NAICS) codes (the most granular sector-level across the US).

From Brynjolfsson et al.'s (2024) dataset, within each sector-year we use the overall share of job postings that are related to digital (computer science and cybersecurity) relative to all job postings.[17] Additional to job postings, this data further outlines "skill clusters" per posting, i.e. does a job posting require specific skills related to 'Information Technology'. We thus also use this more direct measure of digital skill demands by tracking the share of skill clusters related to digital relative to all skill clusters across total job postings.

To contribute to the collection of stylized facts in this paper, Figure 6 shows the distribution of digital occupation demands across sectors. Clearly, demands for digital human capital are highest in digital sectors. This is similar in spirit to our second stylized fact in section 3.2 regarding digital input shares. With this in mind, using the US Bureau of Economic Analysis' (BEA) 'IO Use Before Redefinitions' tables to gauge digital input shares across downstream sectors for the entire US, Figure 7 shows a reasonable correlation between digital human capital and inputs intensity. This provides some evidence for the potential complementarities that exist between digital soft skills and physical tools (Brynjolfsson and Milgrom, 2013).

We run a similar specification to equation (6.1), except we now omit any fixed effects related to state-level variation, given we can only rely on national aggregates, and only include sector and year fixed effects additively (given variation is at the sector-year level):

$$\ln(g_{s,t}) = \gamma_s + \delta_t + \beta \ln(h_{s,t}) + \eta \mathbf{X'}_{s,t} + \varepsilon_{s,t} \tag{6.2}$$

Here, $h_{s,t}$ refers to the aforementioned measures of digital human capital. As usual, $g_{s,t}$ refers to emissions levels, which we source from the U.S. Environmental Protection Agency's (EPA) '2012-2020 Greenhouse Gas National- and State-Level Emission Totals by Industry'. To measure emissions intensity, we try to match industry-level data from the BEA on gross output. The only caveat of this data is that observations are only available at the three-digit NAICS level. This gives us a total of 85 unique sectors.[18] To net out the effect of physical digital inputs versus human capital, in $\mathbf{X'}_{s,t}$ we also include digital input shares as a covariate.

Table 6 provides a fairly consistent suite of null results for the impact of digital human capital on emissions. Regardless of how we measure digital adoption with respect to human capital, either in terms of relative job postings or required skills, no point estimate is statistically significant. This again goes against the intuition that digital capabilities lead to efficiency gains.

[17] Occupational demands concern "(i) all computer occupations (SOC codes beginning with 15), (ii) Cybersecurity occupations, (iii) Machine-Learning-related occupations, (iv) Cloud-related occupations, and (v) NLP-related occupations" (Brynjolfsson et al., 2024, pp. 6-7).

[18] Some sectors were only available at the 2-digit NAICS level, such as construction. We provide further details on data in the Appendix.

(a) Digital Jobs Share **(b)** Digital Skills Share

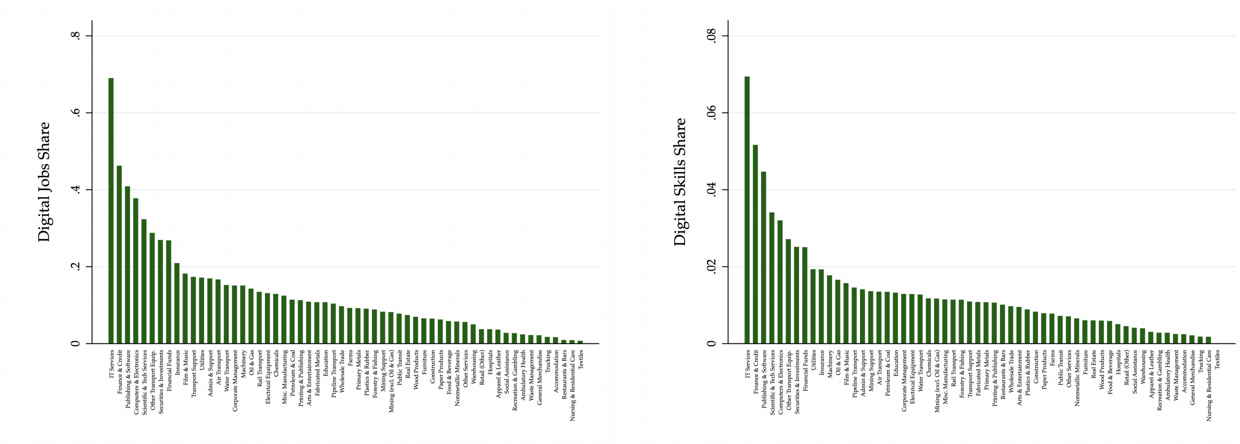


Figure 6: Digital Jobs and Skills Share by Sector

Note: both panels plot averages between 2012-2019. Digital jobs share refers to the share of all job postings within sectors that are classified as a digital occupation. Digital skills share refers to the share of all job postings within sectors that are classified as requiring skills from the digital "skill cluster".

(a) Digital Jobs and Input Share **(b)** Digital Skills and Input Share

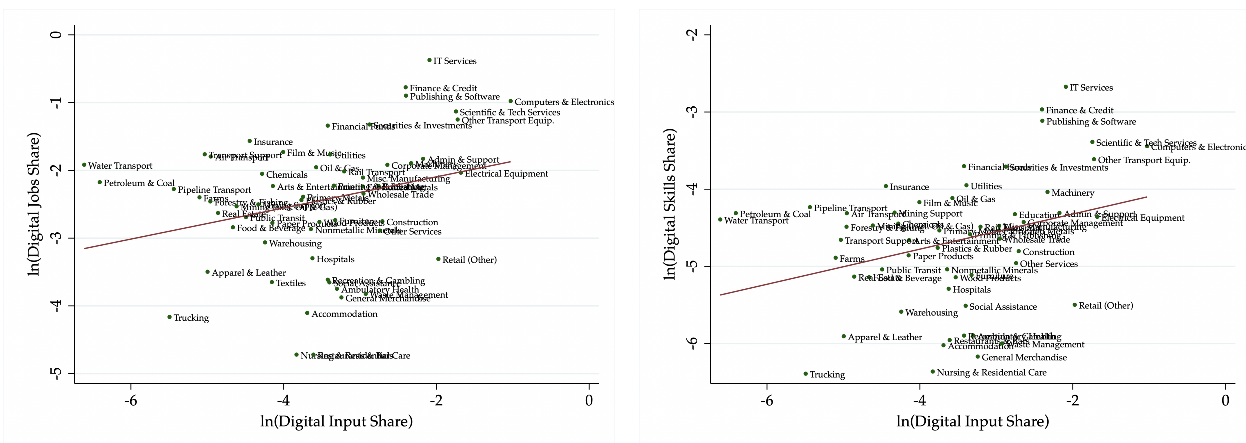


Figure 7: Correlation between Digital Jobs and Skills with Input Shares by Sector

Note: both panels plot averages between 2012-2019. Digital jobs share refers to the share of all job postings within sectors that are classified as a digital occupation. Digital skills share refers to the share of all job postings within sectors that are classified as requiring skills from the digital "skill cluster". Digital input share refers to the share of all inputs within sectors that stem from digital upstream suppliers.

Table 6: Digital Human Capital Results

	(1)	(2)	(3)
Panel A - Digital Jobs	**Total Emissions**	**Total Output**	**Emissions per Unit of Output**
Digital Job Share	-0.034	0.028	-0.061
	(0.087)	(0.047)	(0.087)
Observations	452	452	452
Panel B - Digital Skills			
Digital Skill Share	0.024	0.030	-0.005
	(0.049)	(0.026)	(0.047)
Observations	450	450	450
Panel C - IT Skills			
IT Skill Share	0.005	0.021	-0.016
	(0.084)	(0.047)	(0.084)
Observations	453	453	453
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by sector in parentheses. All outcome variables are logarithmically transformed. Digital job share, digital skill share and IT skill share are also logarithmically transformed. Observations are at the sector-level, defined as 2-digit NAICS codes. All specifications control for digital input shares.

7 Firm-Level Analysis

As a final piece of analysis, we home in on more micro-level evidence, focusing on emissions among firms. Firm-level data allow us to explore how heterogeneity in digital adoption and production practices translates into environmental outcomes at the operational level. Similar to Hege et al. (2025), we use the S&P Global's Trucost Environmental database, which provides emissions by scope at the firm-level across the globe. Reliable data for a somewhat consistent panel of firms is best available from 2010 onwards. This rich database provides various way of measuring digitalization at the firm-level. We outline our various approaches below.

7.1 Measuring Firm-Level Digitalization

Sector-Weighted Digitalization While we have access to firm-level emissions, direct digital adoption of inputs at the firm-level is not as readily available. To go some way in approximating digitalization of inputs among firms, we pursue a similar approach to Nose and Honda (2023) which exploits sector-level digital input shares from the OECD's ICIO tables, as used in sections 4 and 5, weighted by firm size:

$$d_{i,c,s,t>t_0} = \underbrace{\frac{a_{i,c,s,t_0}}{\sum_{j\in\mathcal{F}_{c,s}} a_{j,c,s,t_0}}}_{\text{initial firm size}} \cdot \underbrace{\frac{x^{\text{digital}}_{c,s,t}}{\sum x_{c,s,t}}}_{\text{digitalization}}$$

Here, a given firm i in country c of sector s in year t has digital adoption equal to the product of country-sector level digital input shares and initial firm size, which we measure by initial asset shares of firms. As outlined by Nose and Honda (2023), our firm-level measure of digital adoption rests on the assumption that digitalization is homogeneous within sectors, but diffusion of digital transactions in production scales with firms that make more sales within the same market. We focus on shares within country-sectors, hence we sum over all j firms within the set of country-sectors, $\mathcal{F}_{c,s}$ (where i is allowed to equal j). To ensure that firm size is not driving sector-level digitalization, we use starting values in 2010 (i.e. t_0). Overall, this gives us a sample of approximately 3,400 unique firms across 53 countries since 2010.

Capitalized Software Development For a subset of approximately 700 US firms in the data, we also observe capitalized software development costs, which are expenditures related to creating or acquiring software for internal use or sale. These costs offer a useful proxy for digitalization, reflecting firm-level investment in digital tools, automation, and technology-intensive processes. To again capture digital intensity, we normalize capitalized software expenditures by total assets:

$$d_{i,s,t} = \frac{\text{Capitalized Software Costs}_{i,s,t}}{\text{Total Assets}_{i,s,t}}$$

Firm-Level Digital Supplier Linkages For another subset of US firms, we have access to data on specific firm-to-firm linkages using Compustat's Segments Customer File on approximately 200 firms.[19] This provides information on sales of firms to important customers (defined as those who provide at least 10 percent of a supplying firm's revenue). We subset to supplying firms which we can comfortably locate in the digital sector using NAICS codes, and then for downstream customers calculate the share of all purchases that originate from these firms (the closest approximation to the intermediate input shares in a standard IO table, but now at the firm-level):[20]

$$d_{i,s,t} = \frac{\text{Digital Purchases}_{i,s,t}}{\text{Total Purchases}_{i,s,t}}$$

Overall, based on our classification of digital, we identify 494 supplier firms in the digital sector, out of a total of 2,404 firms with non-missing sales observations in the dataset. When matching

[19] See Carvalho and Voigtländer (2015), Cohen and Frazzini (2008) and Ling et al. (2017) for other studies using this data.

[20] For example, between 2010 to 2019, we can identify that the McDonalds Corporation made purchases from PAR Technology, a company that provides integrated software and hardware solutions for restaurants, including Point of Sale (POS) systems, digital ordering, loyalty programs, and back-office management tools.

with the Trucost Environmental database to then gauge emissions, we obtain an overall sample of 230 firms between 2010-2019.

7.2 Empirical Strategy

For our country-sector-weighted measure of digitalization, we can now run a similar specification to equation (6.1) but include a firm-level fixed effect to capture within-firm changes in digital input adoption and emissions:

$$\ln(g_{i,c,s,t}) = \xi_i + \alpha_{c,t} + \gamma_{c,s} + \delta_{s,t} + \beta \ln\left(d_{i,c,s,t}\right) + \eta \mathbf{X}'_{i,c,s,t} + \varepsilon_{i,c,s,t} \tag{7.1}$$

ξ_i represents the firm fixed effect, thus allowing us to ask the question: if firms digitalize their operations, how does that increase relative emissions within the *same* firm. Similar to equation (3.2), we include our rich set of interactive fixed effects – country-sector, country-year and sector-year –, to absorb as many unobservables as possible. For our outcome variable, $g_{i,c,s,t}$, the data does not provide production-based totals of emissions at the firm-level, as used in sections 4 and 6, but only emissions by scope similar to Table 2: 1, 2 and 3 upstream. Moreover, to measure changes in productivity in addition to emissions intensity, we use data from Compustat on total revenue to proxy for total output.

For capitalized software development and firm-level digital supplier linkages, where we only have access to US data, we run a modified specification from equation (7.1):

$$\ln(g_{i,s,t}) = \xi_i + \delta_{s,t} + \beta \ln\left(d_{i,s,t}\right) + \eta \mathbf{X}'_{i,s,t} + \varepsilon_{i,s,t} \tag{7.2}$$

While we continue to include a firm fixed effect, ξ_i, we now only include sector-year fixed effects, $\delta_{s,t}$, to absorb any sector-level trends. Finally, with respect to estimated effects, given we have three different approaches to measuring the relative intensity of digital input adoption at the firm-level we standardize coefficients for consistent interpretation across measures.

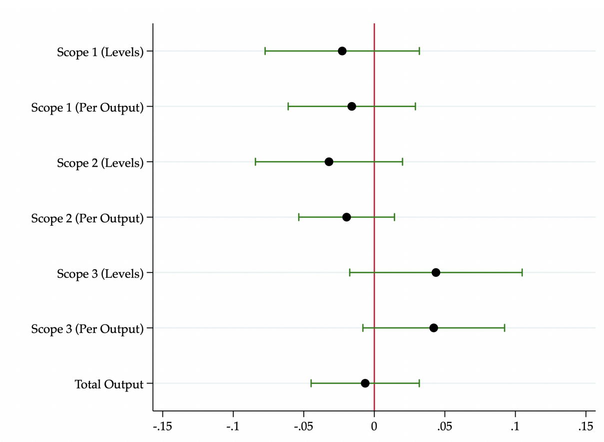
7.3 Firm-Level Results

As per Figure 8, where we standardize coefficients for cleaner interpretation across models, irrespective of how we measure digitalization at the firm-level we continue to find no evidence that digital adoption changes emissions or emissions intensity. In panel (a), when using the global data across just over 3,400 firms, we find limited evidence for any impact on emissions across scopes, in addition to no impact on total output. For scope 1 and 2 emissions, we largely find negative point estimates, whereas for scope 3 we find positive estimates. Yet, these are imprecisely estimated and close to zero in magnitude.

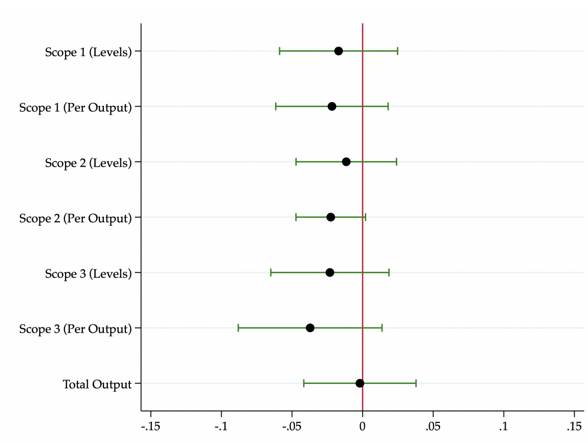
The sector-weighted digitalization measure may be noisier at the firm-level due to relying on aggregate shifts within sectors. Nonetheless, even when focusing on firm-specific digital adoption with regards to capitalized software costs and digital purchases from upstream firms in panels (b) and (c), respectively, we again find limited evidence. Albeit imprecise, the estimates in panel (b) relative to panels (a) and (c) are noticeably all negative, although capitalized software costs may reflect even more measurement error by only capturing the "soft" component of digitalization, ignoring physical inputs such as digital hardware.

The only finding that is almost significant at the 5 percent threshold is scope 2 emissions per unit of output in panel (c) for firm-to-firm digital purchases, where we find a positive point estimate. This effect is largely driven by the positive point estimate for scope 2 emissions in levels, which would feed into the idea that digital inputs themselves require more energy, such as electricity (although this effect itself is insignificant).

(a) Sector-Weighted Digitalization



(b) Capitalized Software Costs



(c) Digital Purchases

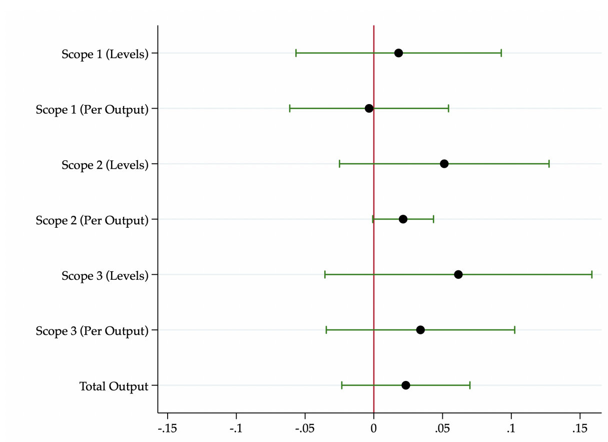


Figure 8: Firm-Level Digitalization and Emissions by Scope

Note: all coefficients are standardized. 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by firm. Only firms with at least 3 years of data are included. For panel (a) we run the specification from equation (7.1) for a sample of approximately 3,400 unique firms. For panels (b) and (c) we run the specification from equation (7.2) for a sample of approximately 700 and 200 unique firms, respectively.

We try a range of robustness checks in Appendix E. First, with regards to the error structure, although we cluster at the firm-level as the unit of analysis with variation, we might think residuals are correlated within country-sectors if there are common sector-level shocks. Second, we might again expect some time lags from digital adoption to have any impact on emissions or output, hence we try specifications with a lag of the digitalization regressor. Finally, while we include firms with at least 3 years of total observations between 2010 to 2019, our estimates may be noisy due to having an unbalanced panel. Albeit at the loss of sample size, when we subset the data to include only those firms with consistent data from 2010-2019 (i.e. a balanced panel), we continue to find similar results to Figure 8.

8 Conclusion

This paper has provided a comprehensive assessment of the popular claim that digitalization – the process of producers adopting more digital inputs into their operations – will decrease greenhouse gas emissions via efficiency gains. No matter how we assess the evidence, from input-output tables across and within countries, to digital human capital or homing in specifically on firms, we find extremely ambiguous support for the "twin transition" hypothesis. If anything, more of our estimates support the finding that there are *increases* in emissions following digitalization. Looking at the various channels suggests part of this is explained by rebound effects through additional output, while little efficiency gains are achieved on aggregate. Regarding emissions by scope, the negative impact appear to be driven mostly by a displacement of emissions towards upstream sectors, i.e., scope 2 and 3 emissions. Overall, our results are consistent with other recent evidence that suggests green innovation has produced limited results with respect to accelerating an overall green transition (Bolton et al., 2023).

Do these results suggest digital adoption and innovation are redundant, and there is simply little that can be done to avail the climate crisis? Despite the evidence in the paper, our answer is likely negative. To be clear, our approach was to look at digitalization and emissions via an economy-wide lens, given this is generally the level of analysis behind claims that digital can decrease emissions *en masse* (e.g. World Economic Forum, 2022). Despite calls for greater R&D investments to promote green innovation (e.g. (Blanchard et al., 2023)), blanket policies to support digital innovation are unlikely to have general equilibrium effects that yield significant decreases in emissions. Nonetheless, this does not mean highly targeted digital innovations cannot play a role in fostering greener consumption and production habits (Lange and Santarius, 2020; Digitalization for Sustainability (D4S), 2022; Muench et al., 2022). For example, smart meters serve as a form of demand management by providing real-time information to both consumers and utilities companies, enabling more efficient energy use, peak load reduction, and better integration of renewable sources. Similarly, dynamic line rating can help optimize energy transmission, reduce the need for investment, and generate net GHG gains. Future research will be needed to study such targeted measures and the magnitude of their potential contributions.

In addition, the results indicating that digitalization induces a displacement of emissions towards upstream input providers, for example through the increased reliance on power-hungry data centers, cloud services, and artificial intelligence models, puts the focus squarely back on the need to decarbonize electricity generation if the environmental promises of the digital sector are to be realized (Bonfiglioli et al., 2025).

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ONLINE APPENDIX
Assessing the Green Digital Transition: Evidence from Input-Output Networks

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Contents

Appendix A Data and Summary Statistics

A.1 Summary Statistics

Table A.1: Summary Statistics of Core Variables

	(1)	(2)	(3)	(4)	(5)
Global (OECD ICIO)	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Total Emissions	85,500	25.02	143.2	0	7,411
Scope 1 Emissions	85,500	8.911	79.92	0	5,238
Scope 2 Emissions	85,500	2.876	25.15	0	2,039
Scope 3 Emissions	85,500	13.23	71.13	0	3,560
Total Output	85,500	29,683	124,946	0	3.700e+06
Digital Input Share	85,500	0.0566	0.0951	0	0.880
China Digital Shock (Upstream)	78,576	0.00860	1.016	-4.390	6.958
China Digital Shock (Downstream)	78,576	0.00592	1.015	-11.39	21.42
US State-Level (Ingwersen et al., 2022)					
Total Emissions	29,562	1.043	5.944	20,730	190.4
Total Output	29,700	9.200e+06	2.124e+07	654.4	4.415e+08
Digital Input Share	29,700	0.0265	0.0317	-0.000658	0.291
Firm-Level (S&P Trucost)					
Scope 1 Emissions	32,420	0.00330	0.0160	0	0.587
Scope 2 Emissions	32,420	0.00220	0.00696	2.37e-08	0.178
Scope 3 Emissions	32,420	0.000453	0.00187	0	0.156
Total Revenue	32,420	781.3	6,595	0.000128	243,771
Digital Input Share	32,420	0.0802	0.131	0.000262	0.762
Capitalized Software Costs/Total Assets	2,741	0.0161	0.0242	0	0.239
Digital Purchases Share	4,341	0.159	0.341	0	1.000

Note: summary statistics are taken between: 1995-2019 for the global data, 2012-2019 for the US state-level data, and 2010-2019 for the firm-level data. Emissions refer to million tonnes and for output refer to thousands USD.

Appendix B TWFE Robustness Checks

B.1 Lagged Effects

Table B.1: Static Fixed Effects Results with Lags

	(1)	(2)	(3)
Panel A - One Year Lag	**Total Emissions**	**Total Output**	**Emissions per Unit of Output**
Digital Input Share	-0.004	-0.016**	0.014*
	(0.010)	(0.008)	(0.008)
Observations	82,969	83,219	82,969
Panel B - Five Year Lag			
Digital Input Share	-0.001	-0.002	0.002
	(0.009)	(0.008)	(0.007)
Observations	69,699	69,901	69,699
Country $\times$ Sector FE	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes
Sector $\times$ Year FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by country-sector in parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed.

B.2 Dropping Units

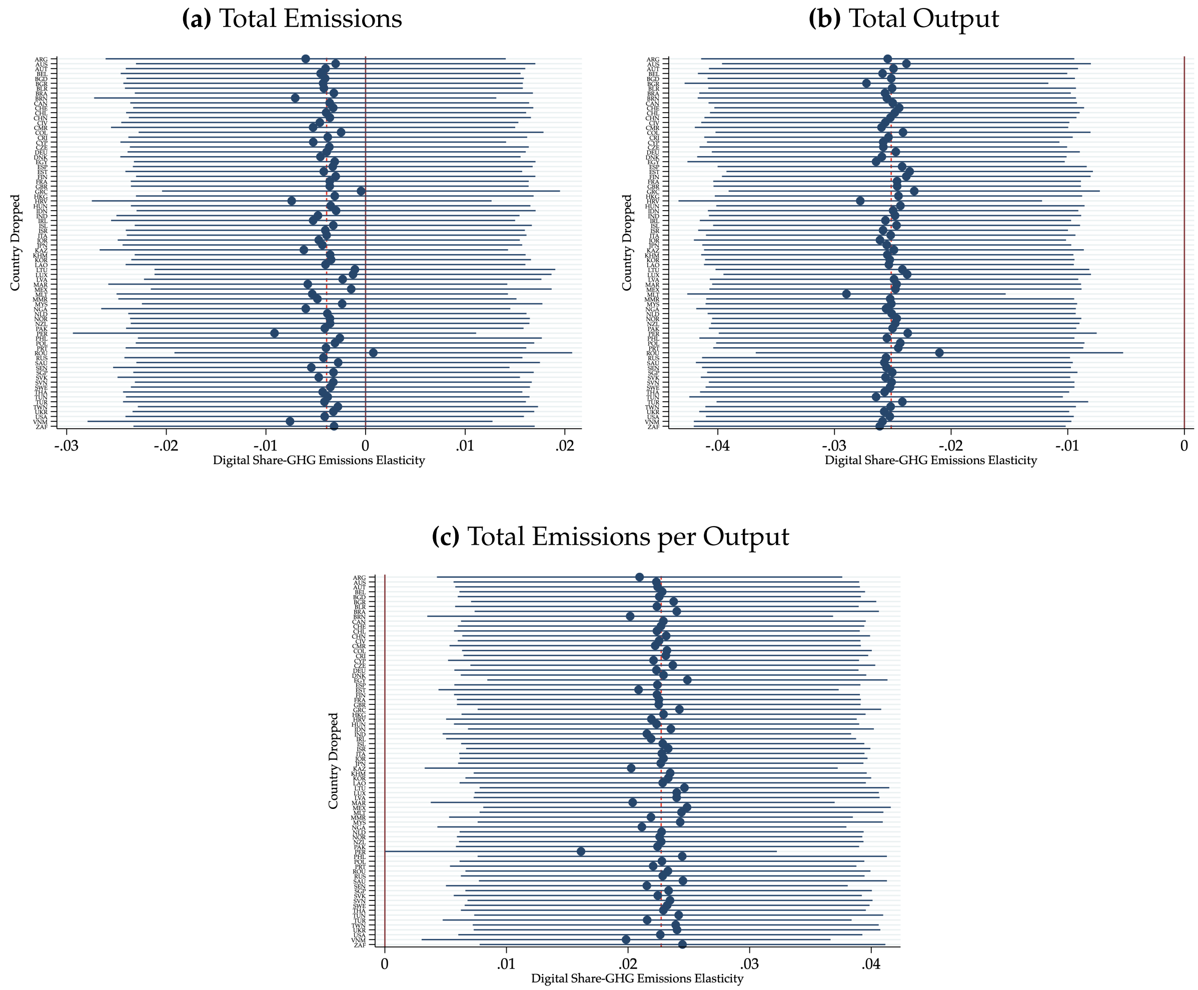
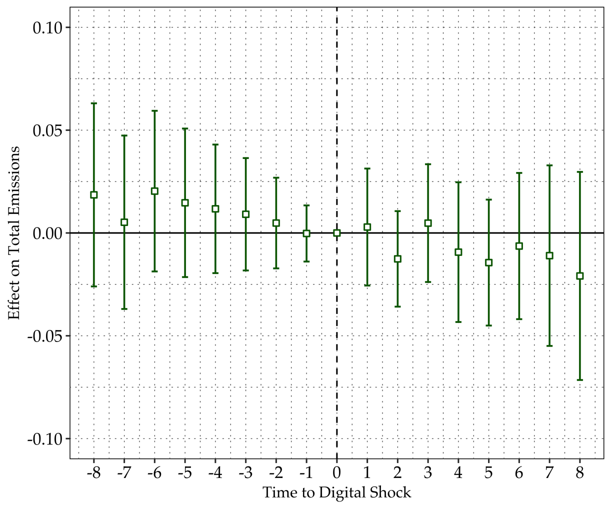


Figure B.1: Dropping Countries

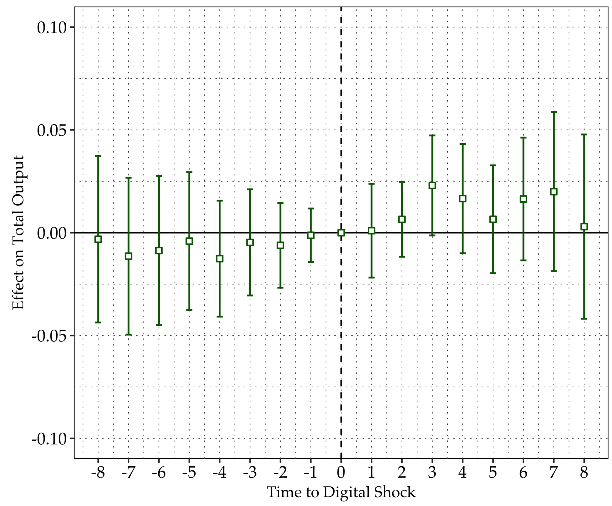
Note: 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by country-sector.

B.3 Event Study for Dynamic Effects

(a) Total Emissions



(b) Total Output



(c) Total Emissions per Output

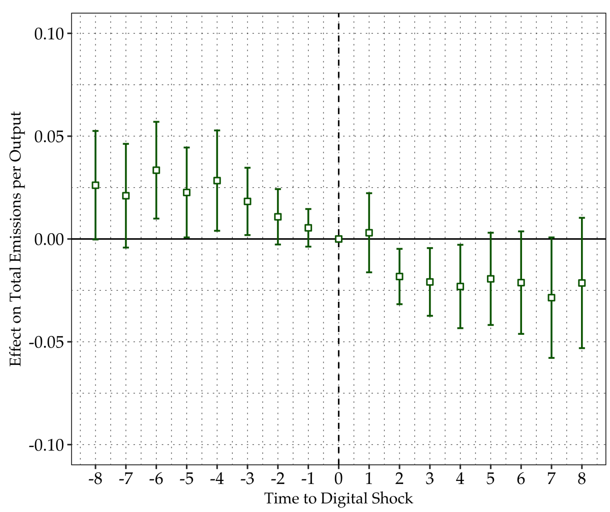


Figure B.2: Firm-Level Digitalization and Emissions by Scope

Note: 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by country-sector.

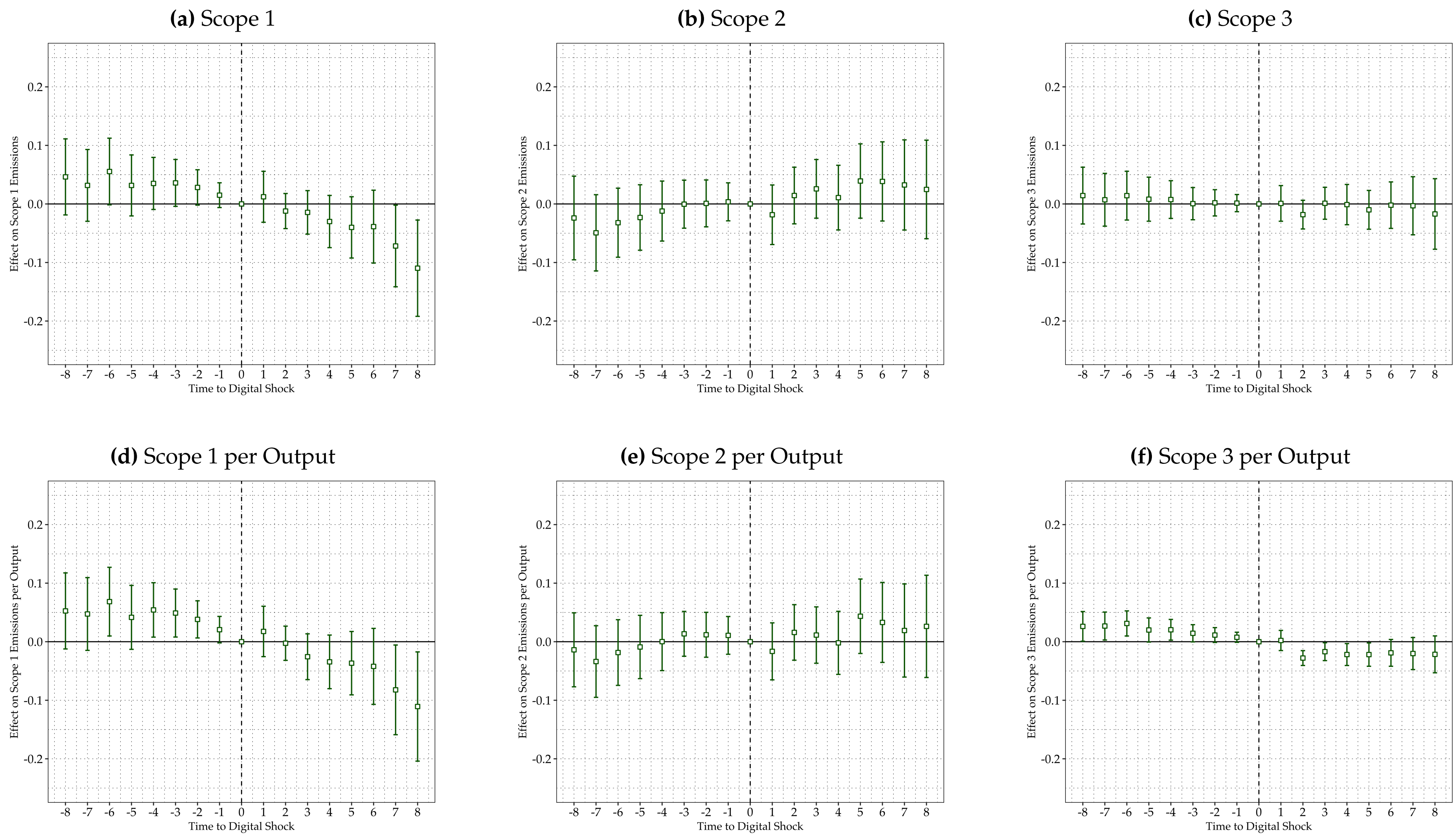


Figure B.3: Event Study Results for Emissions by Scope

Note: 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by country-sector.

Appendix C Model Extension

Here we provide slightly richer micro-foundations in the CES production function. Denote output as a choice between labor, L_i, and inputs, X_i:

$$Y_i = \left(\alpha_i L_i^{\xi_i} + (1-\alpha_i)X_i^{\xi_i}\right)^{\frac{1}{\xi_i}}, \text{ where } \sigma_i = \frac{1}{1-\xi_i}$$

α_i is a preference weight, and σ_i is the elasticity of substitution. We can further define inputs as a combination of intermediate inputs across digital, $\mathcal{D}$, and non-digital, $\mathcal{D}'$, sectors:

$$\begin{aligned} X_i &= \left(\sum_{j=1} \rho_{ij} X_{ij}^{\frac{\eta_i-1}{\eta_i}}\right)^{\frac{\eta_i}{\eta_i-1}} \\ &= \left(\sum_{j\in\mathcal{D}} \rho_{ij} X_{ij}^{\frac{\eta_i-1}{\eta_i}} + \sum_{j\in\mathcal{D}'} \rho_{ij} X_{ij}^{\frac{\eta_i-1}{\eta_i}}\right)^{\frac{\eta_i}{\eta_i-1}} \\ &= \left(D_i^{\frac{\eta_i-1}{\eta_i}} + N_i^{\frac{\eta_i-1}{\eta_i}}\right)^{\frac{\eta_i}{\eta_i-1}} \end{aligned}$$

Here, ρ_{ij} is a preference/share parameter across inputs, and η_i is the elasticity of substitution. Suppose composite inputs are themselves comprised of domestic, d, and foreign, f, inputs:

$$X_{ij} = \left[\beta_{ij}(x_{ij}^d)^{\frac{\varsigma_{ij}-1}{\varsigma_{ij}}} + (1-\beta_{ij})(x_{ij}^f)^{\frac{\varsigma_{ij}-1}{\varsigma_{ij}}}\right]^{\frac{\varsigma_{ij}}{\varsigma_{ij}-1}}$$

Domestic and foreign inputs of sector j have prices p_j^d and p_j^f, respectively. We can thus solve for the price index of intermediates, X_{ij}:

$$P_{ij} = \left[\beta_{ij}(p_j^d)^{1-\varsigma_{ij}} + (1-\beta_{ij})(p_j^f)^{1-\varsigma_{ij}}\right]^{\frac{1}{1-\varsigma_{ij}}}$$

Again, β_{ij} is a preference parameter over domestic and foreign inputs within the same sector, and ς_{ij} is the elasticity of substitution between those inputs. Going back to the composite intermediate input, X_i, we can now further solve for the price index, whereby:

$$P_{X,i} = \left(\sum_{j\in\mathcal{D}} \rho_{ij} P_{ij}^{1-\eta_i} + \sum_{j\in\mathcal{D}'} \rho_{ij} P_{ij}^{1-\eta_i}\right)^{\frac{1}{1-\eta_i}}$$

This suggests total purchases of digital inputs as a share of total inputs equals:

$$d_i = \frac{\sum_{j\in\mathcal{D}} X_{ij} P_{ij}}{X_i P_{X,i}}$$

From this set-up, firms within sector j first make the choice of whether to source inputs from domestic or foreign sectors. Second, they must then decide how much to employ inputs across digital and non-digital sectors. The final choice then consists of choosing labor versus intermediates for final production. Digital input intensity, d_i, now written in terms of sales versus quantity share, is determined by foreign and domestic prices both within and across sectors.

We can finally solve for marginal cost of output. If labor earn wages w_i, and we know the price of inputs, P_{X_i}, then the standard CES result is:

$$P_{Y,i} = \left[\alpha_i w_i^{1-\sigma_i} + (1-\alpha_i) P_{X,i}^{1-\sigma_i}\right]^{\frac{1}{1-\sigma_i}}$$

With respect to technical coefficients, we can thus write total expenditure as a share of total revenue:

$$a_{ij} = \frac{P_{ij} X_{ij}}{P_{Y,i} Y_i}$$

It is now easy to re-define emissions using the above set-up, although given d_i refers to expenditure versus quantity shares, we must scale emissions with respect to expenditure and not just quantity:

$$E_i = \Delta(d_i) \left[\tilde{\phi}_N + (\tilde{\phi}_D - \tilde{\phi}_N) d_i\right] P_{X_i} X_i,$$

Here, $\tilde{\phi}_{\{D,N\}}$ has the same definition as in the paper, comprising direct and indirect emissions, except now $\phi_D = \frac{\sum_{j \in \mathcal{D}} \phi_j X_{ij} P_{ij}}{\sum_{j \in \mathcal{D}} X_{ij} P_{ij}}$ and $\phi_N = \frac{\sum_{j \in \mathcal{D}'} \phi_j X_{ij} P_{ij}}{\sum_{j \in \mathcal{D}'} X_{ij} P_{ij}}$, such that direct emissions are a share of total expenditures across inputs in digital and non-digital sectors. ϕ_j can thus be interpreted in terms of emissions per dollar of expenditure.

Appendix D Shift-Share Instrument Robustness Checks

D.1 Digital Input Adoption and Divergence

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Digital Input Share)					
ln(Digital Input Share)$_{1995}$	0.439***	0.439***	0.223***	0.223***	0.447***	0.447***
	(0.021)	(0.021)	(0.058)	(0.071)	(0.021)	(0.021)
Observations	79,793	79,793	5,472	5,472	74,321	74,321
R^2	0.772	0.798	0.581	0.692	0.711	0.747
Country FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Sector FE	Yes	No	Yes	No	Yes	No
Country $\times$ Year FE	No	Yes	No	Yes	No	Yes
Sector $\times$ Year FE	No	Yes	No	Yes	No	Yes
Sector	All	All	Digital	Digital	Non-Digital	Non-Digital

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by country-sector in parentheses. ln(Digital Input Share)$_{1995}$ refers to initial digital input intensity in 1995 (which is time-invariant, hence the omissions of a country-sector fixed effect). Columns 1-2 use all sectors. Columns 3-4 use only sectors classified as digital from the OECD inter-country input-output data, i.e. 'Computer, electronic and optical equipment', 'Telecommunications' and 'IT and other information services'. Columns 5-6 use all sectors that are non-digital. All specifications only include years 1996 onwards.

D.2 2SLS Results Interpretation

Recall the first-stage specification is:

$$\ln\left(d_{c,s,t}\right) = \alpha_{c,t} + \gamma_{c,s} + \delta_{s,t} + \xi^{\text{down}} Z^{\text{down}}_{c,s,t-1} + \xi^{\text{up}} Z^{\text{up}}_{c,s,t-1} + \eta \mathbf{X}'_{c,s,t-1} + u_{c,s,t-1}$$

The second-stage specification is:

$$\ln(g_{c,s,t}) = \alpha_{c,t} + \gamma_{c,s} + \delta_{s,t} + \beta \ln(d_{c,s,t}) + \eta \mathbf{X}'_{c,s,t} + \varepsilon_{c,s,t},$$

The reduced-form effects from the upstream and downstream shocks vis-á-vis China's digital expansion can be represented as $\theta^{\{\text{down,up}\}}$. Further, denote $\sim$ above variables as residualized versions used in the first and second-stage specifications, where we apply the FWL theorem to purge all variables of all fixed effects.

Using the standard result for 2SLS estimators (Wooldridge, 2010), we can define the following:

$$\widehat{\beta}_{\text{2SLS}} = \frac{\left[\xi^{\text{up}}\text{Var}(\tilde{Z}^{\text{down}}) + \xi^{\text{down}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\theta^{\text{up}} + \left[\xi^{\text{down}}\text{Var}(\tilde{Z}^{\text{up}}) + \xi^{\text{up}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\theta^{\text{down}}}{\left[\xi^{\text{up}}\text{Var}(\tilde{Z}^{\text{down}}) + \xi^{\text{down}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\xi^{\text{up}} + \left[\xi^{\text{down}}\text{Var}(\tilde{Z}^{\text{up}}) + \xi^{\text{up}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\xi^{\text{down}}}$$

Given we estimated that the reduced-form effect from the upstream shock was zero, $\theta^{\text{up}} \approx 0$, then we can re-write the 2SLS estimate as:

$$\widehat{\beta}_{\text{2SLS}} \approx \frac{\left[\xi^{\text{down}}\text{Var}(\tilde{Z}^{\text{up}}) + \xi^{\text{up}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\theta^{\text{down}}}{\left[\xi^{\text{up}}\text{Var}(\tilde{Z}^{\text{down}}) + \xi^{\text{down}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\xi^{\text{up}} + \left[\xi^{\text{down}}\text{Var}(\tilde{Z}^{\text{up}}) + \xi^{\text{up}}\text{Cov}(\tilde{Z}^{\text{up}}, \tilde{Z}^{\text{down}})\right]\xi^{\text{down}}}$$

This provides a formal, statistically-grounded explanation for why only the downstream (i.e. supply-side) component of the China digital shock is relevant in estimating the impact of digital input intensity on emissions and output. This is what we would expect if China's expansion as a global exporter of digital inputs, especially to non-regional trading partners of the same sector, serves as a supply-side shock on a given country-sector's upstream suppliers.

D.3 Dropping Units

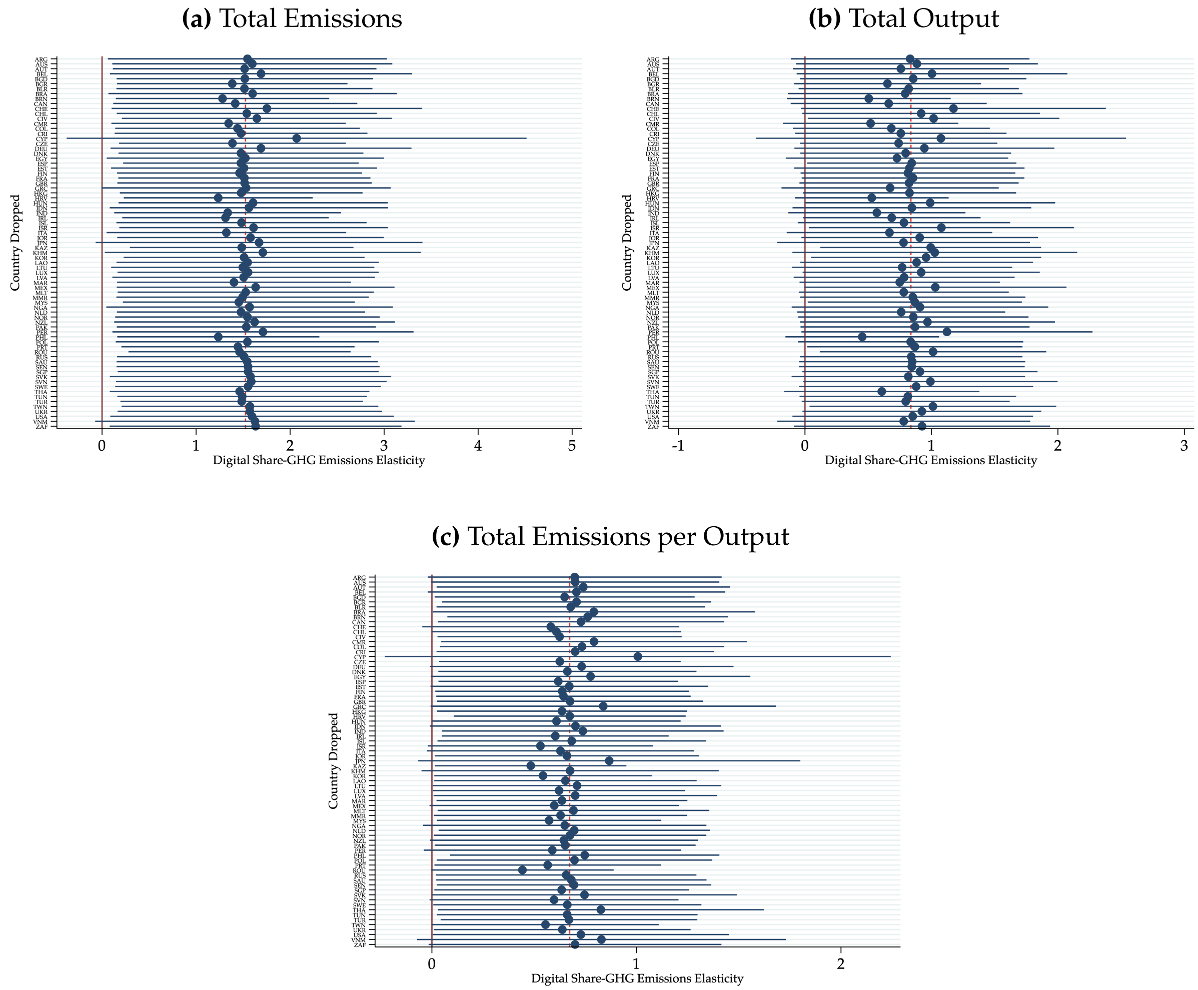


Figure D.1: Dropping Countries

Note: 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by country-sector.

D.4 Omitting Trade in Services

Table D.1: Shift-Share IV Results

	(1)	(2)	(3)
	Total Emissions	**Total Output**	**Emissions per Unit of Output**
Panel A - Second Stage			
Digital Input Share$_t$	0.950**	0.315	0.569***
	(0.365)	(0.204)	(0.220)
	[0.848, ∞]	[∞, ∞]	[0.261, ∞]
Panel B - First Stage	**Dependent variable is Digital Input Share$_t$**		
China Shock (Downstream)$_{t-1}$	0.017**	0.016**	0.017**
	(0.007)	(0.007)	(0.007)
China Shock (Upstream)$_{t-1}$	-0.024**	-0.023**	-0.024**
	(0.012)	(0.012)	(0.012)
Panel C - Reduced Form	**Total Emissions**	**Total Output**	**Emissions per Unit of Output**
China Shock (Downstream)$_{t-1}$	0.027***	0.014***	0.012***
	(0.005)	(0.004)	(0.003)
China Shock (Upstream)$_{t-1}$	-0.002	0.009	-0.009
	(0.008)	(0.006)	(0.006)
F-test (effective)	4.411	4.212	4.411
F-test (Anderson-Rubin)	17.437	10.136	9.650
[p-value]	[0.000]	[0.000]	[0.000]
Observations	75,215	75,294	75,215
Country $\times$ Sector FE	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes
Sector $\times$ Year FE	Yes	Yes	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by country-sector in parentheses across all panels. In the second stage (panel A), Anderson-Rubin confidence intervals are also reported in square parentheses. All outcome variables are logarithmically transformed. Digital input share is also logarithmically transformed. Panel A outlines results from the second stage. Panel B outlines results from the first stage. Panel C outlines reduced form results. F-test (effective) refers to the test statistic from Olea and Pflueger (2013). F-test (AR) refers to the Anderson-Rubin F-statistic.

Appendix E Firm-Level Robustness Checks

E.1 Alternative Standard Errors

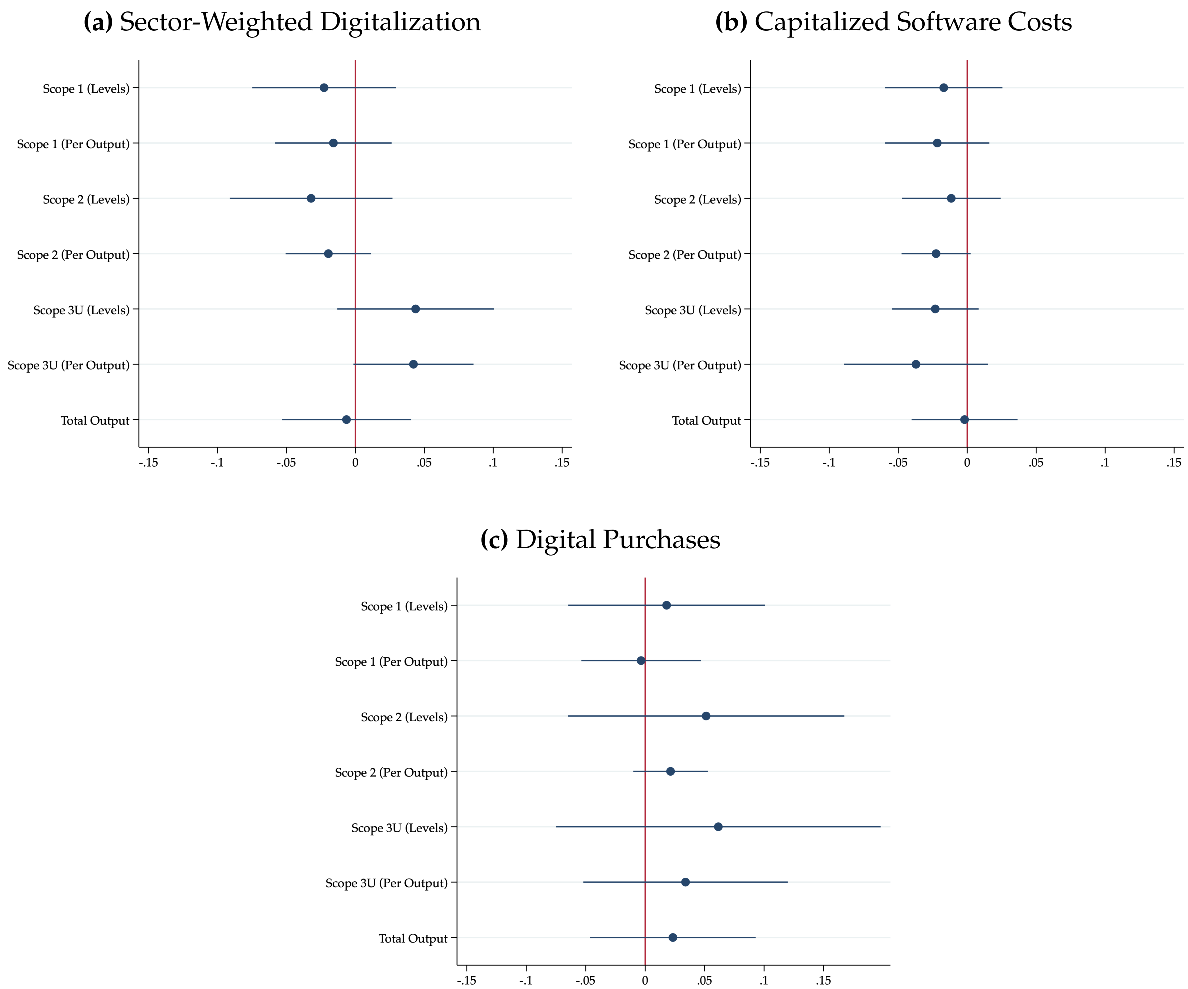
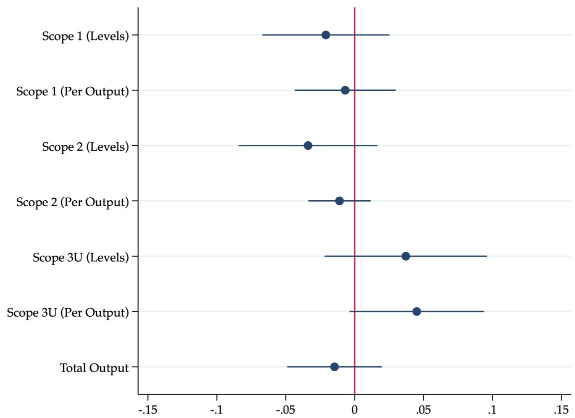


Figure E.1: Firm-Level Digitalization and Emissions by Scope (Alternative SEs)

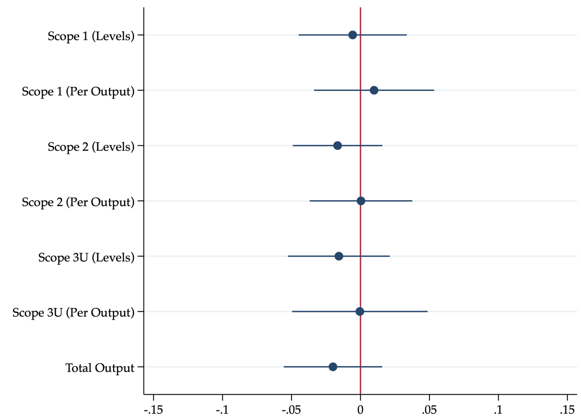
Note: all coefficients are standardized. 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by country-sector (Figure 8 of the paper clusters standard errors by firm). Only firms with at least 3 years of data are included.

E.2 Lagged Effects

(a) Sector-Weighted Digitalization



(b) Capitalized Software Costs



(c) Digital Purchases

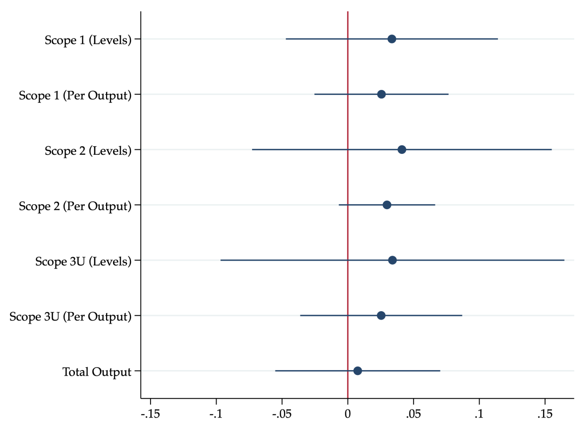


Figure E.2: Firm-Level Digitalization and Emissions by Scope (Lagged Effects)

Note: all coefficients are standardized. 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by firm. We lag digital input adoption across all three approaches by one year. Only firms with at least 3 years of data are included.

E.3 Balanced Panel

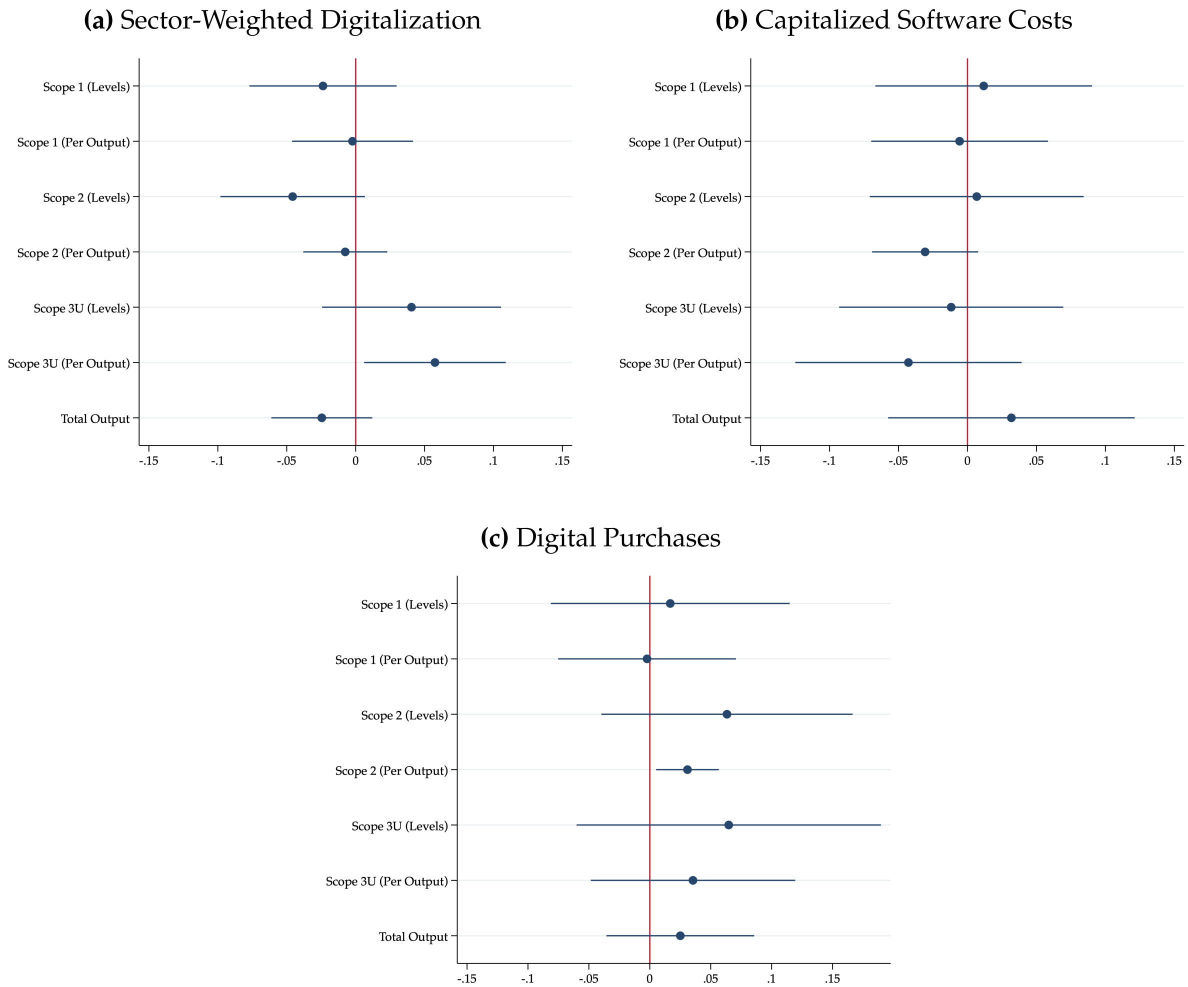


Figure E.3: Firm-Level Digitalization and Emissions by Scope (Balanced Panel)

Note: all coefficients are standardized. 95% confidence intervals and point estimates are plotted, with robust standard errors clustered by firm. Only firms with at least 10 years of data are included.

References

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