A Few Good Masks:
Evidence from Mask Manufacturing in Rwanda during the COVID-19 Pandemic*

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Abstract

Can trade frictions limit access to improved health technologies? Rwanda encouraged and licensed domestic production of high-quality masks by a few selected textile manufacturers at the start of the COVID-19 pandemic. We exploit spatial variation in exposure to mask manufacturing through pre-licensing medical and textile trade networks within an event-study design using receipt-level transaction data. Local markets less exposed to mask manufacturing had higher mask prices, purchased fewer masks, and experienced faster growth in COVID-19 infections proxied by demand for anti-fever medicine. The dynamics of our results suggest that mask quality, rather than quantity, explains reduced infections caused by manufactured masks.

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Introduction

In this paper, we study the impacts of trade frictions on health through access to health technologies in the context of mask manufacturing during the COVID-19 pandemic in Rwanda. We exploit spatial variation in exposure to domestic mask manufacturing through supply networks generated by a policy that licensed a selected few domestic textile manufacturers to produce masks. We estimate an event study design using receipt-level transaction data and find access to manufactured masks decreased mask prices, increased purchased quantities of domestically manufactured masks, and reduced COVID-19 infections; the dynamics of our results suggest that increased mask quality, rather than quantity, explains reduced infections caused by manufactured masks.

Masks are an important non-pharmaceutical intervention to slow the spread of viral airborne pathogens such as COVID-19 (Abaluck et al., 2020; Howard et al., 2021). Yet, concerns over mask availability shaped public health recommendations on a global scale, with the World Health Organization avoiding recommending healthy individuals wear masks during early stages of the pandemic due to limited supply (World Health Organization, 2020). Sharp increases in global demand for masks following the rapid onset of the pandemic generated fear that supply was insufficient and triggered export restrictions to protect domestic access (Carreño et al., 2020).

Against this background of limited mask supply and export restrictions, sub-national trade frictions had the potential to generate regional inequities in access to masks, and in turn the spread of COVID-19. The burden of import restrictions on masks was likely greatest in developing countries with limited domestic mask manufacturing (Abaluck et al., 2021), and where international trade frictions may compound with substantial domestic trade frictions (Atkin & Donaldson, 2015; Donaldson, 2018). Yet, there is no direct evidence that trade frictions impact health through access to health technologies, including masks; such evidence would complement recent work estimating sub-nationally unequal impacts of trade on health with employment (Dorn et al., 2019; Pierce & Schott, 2020) and pollution (Bombardini & Li, 2020) as mechanisms.

We produce causal estimates of the impacts of mask access at the onset of the COVID-19 pandemic in the context of Rwanda. On April 17, 2020, the Rwanda Food and Drug Administration (FDA) granted initial licenses to selected garment manufacturers to produce masks. This policy was accompanied by a certification process, ensuring that all formally traded masks met FDA filtration standards.[1] We observe that sub-Districts are more likely to source masks from the same sub-Districts they purchased textiles from before the mask licensing policy came into effect. Since not all textile producers were licensed to produce masks in the first months of the policy, this mechanically generated uneven access to domestically manufactured masks across sub-Districts. Yet, the shape of textile supply chains pre-COVID-19 does not predict pre-licensing changes in outcomes. This suggests sub-Districts that, before COVID-19, sourced disproportionately more non-mask textiles from high and low mask manufacturing intensity sub-Districts, would have experienced the same post-licensing changes in outcomes if there was no domestic mask manufacturing. We use this observation to construct a shift-share (Goldsmith-Pinkham et al., 2020) measure of exposure to licensed domestic mask manufacturing, based on purchases by destination sub-Districts of non-mask textiles from origin sub-Districts with high and low mask manufacturing intensity.

We construct high-frequency panel data on inter-sub-District product trade, including prices and sales of masks, using the universe of timestamped transactions made through Electronic Billing Machine (EBM) software from November 2019 through April 2021. For each transaction we observe firm identifiers, product information, prices, and quantities, for sales to both final consumers and to firms. We produce the following four key results.

First, we find that variation in access to licensed domestically manufactured masks generated by trade frictions affected mask prices – a one standard deviation increase in exposure to mask manufacturing persistently reduced mask prices by 7.5%, which corresponds to 20% of a large increase in mask prices in Rwanda that followed the start of the COVID-19 pandemic. These impacts on prices persisted to the end of our study period; this suggests that variation in exposure is driven by variation in domestic trade frictions, which generated persistent decreases in mask prices in sub-Districts more exposed to licensed mask manufacturing.

Second, we show that, while exposure to licensed domestic mask manufacturing increased purchased quantities of domestically manufactured masks, these effects dissipate rapidly. Our preferred estimates imply a price elasticity of demand for masks of -2.1 before the introduction of universal quality standards in June. This elasticity is

[1] Formally traded masks comprise both domestically manufactured and imported masks.

modestly higher than demand elasticities for other durable preventive health products (Berry et al., 2020); we interpret this as driven by the availability of a close substitute for formally traded masks in these early months of the pandemic—informally produced non-certified masks, which we do not observe in our data on formal transactions. In contrast, following the June gazetting of a decree requiring that all masks sold in Rwanda meet the same quality standards as certified manufactured masks, which targeted the informal sale of non-certified masks, this elasticity converges towards zero. We interpret this fade-out as driven by substitution away from informal low-quality masks in low-exposure sub-Districts to formally manufactured masks following the decree.

Third, access to licensed domestically manufactured masks slowed the spread of COVID-19. As an alternative to sub-District data on COVID-19 cases, we use EBM data on purchases of fever medicine as a proxy for active COVID-19 infections. We find a one standard deviation increase in manufactured mask exposure initially reduced the monthly growth rate of infections by 2.9%; following the introduction of universal quality standards, we find no further impacts on growth rate, while level impacts on infections persisted. The implied impacts of certified masks on the transmission of COVID-19, the first in the context of Sub-Saharan Africa, are comparable to existing work in the United States (Chernozhukov et al., 2021) and rural South Asia (Abaluck et al., 2021). Our results also contribute more broadly to a literature that estimates the impacts of preventive health interventions at scale (Miguel & Kremer, 2004; Bleakley, 2007, 2010); a counterfactual with reduced domestic mask manufacturing suggests large benefits of licensing, with averted hospitalization costs an order of magnitude larger than fiscal costs.

Lastly, the dynamics of our results suggest that mask quality, as opposed to increased mask use, explains the impact on COVID-19 infections. While we do not directly observe mask quality, we no longer see impacts of early exposure to licensed manufacturing on the spread of COVID-19 after the June decree introducing universal quality standards, just as the impacts on certified manufactured mask purchases fade out. In contrast, our impacts on prices persist, while we would expect a reduction in prices to drive any use channel. Anecdotal evidence also supports mask quality as a channel. Mask use was high, even before the June decree, as starting April 19 Rwanda had strict enforcement of mask mandates and near-universal compliance. However, prior to the June decree, standards for mask quality were only implemented by, and enforced for, licensed mask manufacturers; masks meeting these standards display much greater aerosol filtration (Konda et al., 2020). These results imply policies that increase the supply of certifiably high-quality masks are strongly complementary to policies that increase mask use (Abaluck et al., 2021).

The rest of the paper is structured as follows. Section 1 describes the data and the policy environment; Section 2 describes our identification and empirical strategy, and presents our estimates of impacts of domestic certified mask manufacturing; and Section 3 concludes.

1 Data and context

1.1 Data

We use multiple administrative data sources to study the market for masks at the outset of the pandemic in Rwanda. Our study sample begins in November 2019 and extends through April 2021, one year following the licensing of mask manufacturers. In this section, we briefly describe each dataset, its coverage, and the construction of its associated variables, with additional details left to Appendix A.

EBM Our primary source of data is the universe of digitally signed and timestamped software issued EBM receipts collected by Rwanda Revenue Authority (RRA) between November 2019 and April 2021, allowing us to track product-level sales between firms and final consumers. EBMs record receipts issued by businesses to support the collection of VAT in Rwanda, and are mandated for use by VAT taxpayers. In November 2019, these data recorded 81.8 billion Rwandan Francs (RwF) of value added, equivalent to 10.4% of monthly GDP or 16.9% of VAT declared turnover.

We leverage these receipts to construct firm-product transaction-level data on prices and quantities. First, each EBM is identified by a unique Sales Data Controller (SDC) identifier, which we link to Taxpayer Identification Numbers (TIN) and, in turn, firm registration data to identify selling firms. When a receipt is issued for a sale to other VAT taxpayers, purchasing firms must provide their TIN. To construct the sub-District of both buyers and sellers, we assume that non-VAT taxpayer final consumers are located in the same sub-District as the selling firm. For the majority of our analysis, we aggregate data to the buyer sub-District, which constitutes credible markets; the average sub-District has a population of 32,000 individuals and 1,000 registered firms. Second, for each transacted item on a receipt, we observe a product-classification UNSPSC code and a string description; we use these to identify textile products and masks, and we construct firm-product identifiers using the selling firm and product string description pair. Third, we classify masks as manufactured when sold by a firm that was issued a mask manufacturing license from the FDA. In Section 2.1.1, we use this data on mask and textile purchases and sales to construct sub-District mask manufacturing exposure; our primary analysis sample comprises the 239 sub-Districts for which we observe non-mask textile purchases necessary to construct mask manufacturing exposure.

We observe over 75,000 transactions covering nearly 5,000,000 masks, approximately 1.6 masks per adult in our primary analysis sample. On average, prices are 680 RwF (0.66 USD) per mask.[2] Production of masks is spatially concentrated relative to consumption; aggregating to the sub-District level, the average purchasing (selling) sub-District buys from (sells to) 2.1 (16.4) sub-Districts.

Customs We construct measures of border prices of masks using customs data containing the universe of imports by Rwandan firms. Just as for EBM, we identify mask imports using a combination of product codes and product string descriptions, and all imports are timestamped. We then use the combination of the point of entry and the TIN of the importing firm as identifiers to construct an equivalent of firm-product.

Firm registration data We construct firm characteristics using formal registrations of firms. Each firm is identified by a unique TIN, and the registrations contain the firm's ISIC sector classification (which we use to identify textile manufacturers) and sub-District.

Census We construct data on socioeconomic characteristics of sub-Districts using the 2012 Population and Housing Census.

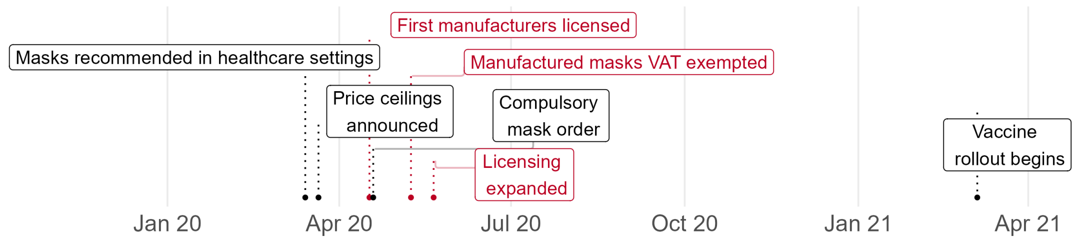
[2] Basic descriptive statistics from the EBM data, and additional details on its coverage and construction, are presented in Appendix A.1.

1.2 Context

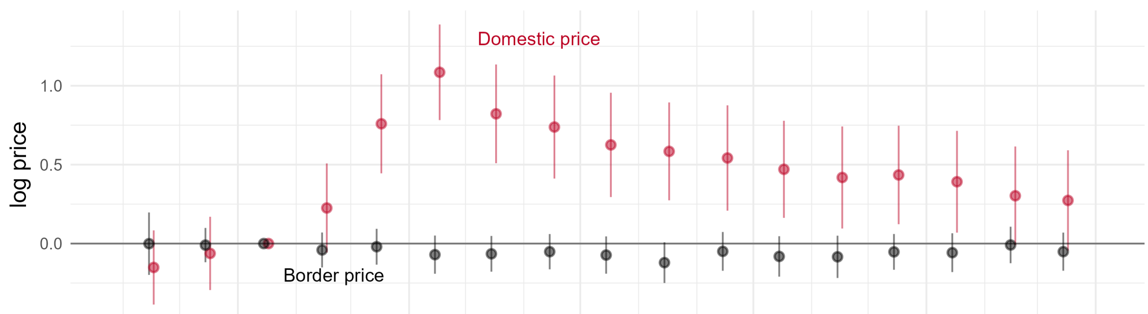
Our analysis of the impacts of mask manufacturing covers the early stages of the COVID-19 pandemic in Rwanda. We present the timeline of key events and policies that relate to the mask mandate in Figure 1a, leveraging fortnightly cabinet announcements and daily COVID-19 updates. The Ministry of Health (MINISANTE) announced the first case of COVID-19 in Rwanda on March 14, 2020, and recommended the use of masks in health care settings. On March 22, the Prime Minister announced a lockdown including school closures, the suspension of international travel, a work-from-home mandate, and the prohibition of non-essential movement, all with meaningful impacts on economic activity (Byrne et al., 2021). A compulsory mask mandate for all public settings was introduced on April 19, just before lockdown restrictions were partially lifted on May 4. This mandate was strictly enforced: deterrence measures included fines in Kigali City Province, and complementary measures to promote compliance included infomercials by the national broadcaster and education campaigns by the Rwanda National Police. These measures were effective—by early June, according to the Innovations for Poverty Action's RECOVR survey, 95% of households always wore a mask when they went out in public.

Figure 1: Timeline

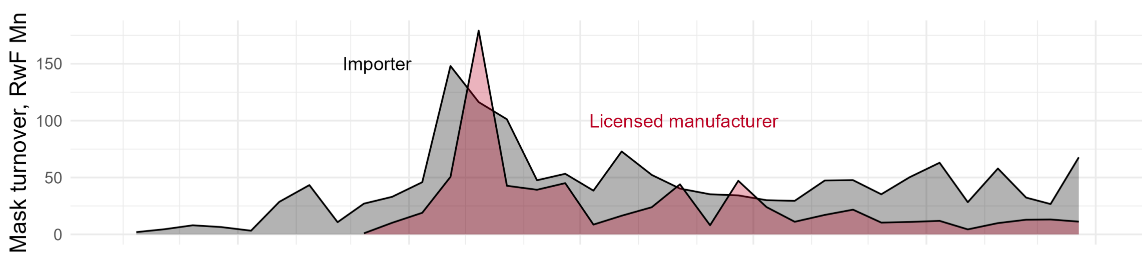
(a) Mask & health policy



(b) Domestic and border prices



(c) Mask turnover at mask importers and manufacturers



Notes: Figure 1a presents a timeline of mask (in red) and mask manufacturer (in black) policies in Rwanda during our study period. Figure 1b presents a monthly time series of log changes in import (in red) and domestic (in black) mask prices relative to January 2020. Figure 1c presents a bimonthly time series of mask turnover at importers (in red) and manufacturers (in black).

Domestic mask manufacturing To increase the availability of certifiably high-quality masks, the Rwanda FDA issued licenses to a few selected textile manufacturers to produce surgical and barrier masks. We present the timeline of key policy actions targeting the manufacturing of certified masks in Rwanda in Figure 1a. On March 21, 2020, in response to reported shortages of imported masks, the Ministry of Trade and Industry (MINICOM) imposed price restrictions and the FDA issued a public announcement citing concerns about the sale of substandard masks. To combat this shortage and to mitigate concerns about the sale of unregulated low-quality masks, the FDA licensed 21 garment manufacturers that had submitted applications to produce masks on April 17, two days before the national mask mandate. Licensing was coupled with additional incentives to engage in mask production—MINICOM announced the intent to facilitate access to machines and raw materials, and a VAT exemption for domestically manufactured masks was granted by the Ministry of Finance and Economic Planning on April 30.

To ensure masks minimized transmission of COVID-19, quality standards were progressively scaled up, starting with licensed manufacturers and eventually covering all mask sales nationally. As part of the April 17, 2020 licensing of textile manufacturers to produce masks, the FDA enforced quality standards on manufacturers through direct assessments of manufactured mask quality. These standards included specifications for filtration, penetration, and breathability of masks, and were consistent with product characteristics known to maximize aerosol filtration efficiency (Konda et al., 2020). Similar standards were gazetted into law in June, covering all masks and manufacturers. These standards constituted the benchmark for subsequent audits. Similar to enforcement in the earlier months of the pandemic, licensed manufacturers submitted their masks to quality assurance tests prior to leaving the factory. Firm audits were supplemented by retailer audits, and substandard masks identified by audits were removed from markets. In line with the gazetted guidelines, compliant masks were affixed with an RSB standardization mark. We present additional details on these requirements and specifications and enforcement in Appendix B.

1.3 Descriptive evidence on domestic mask manufacturing and mask prices

To motivate our analysis of the impacts of exposure to domestic mask manufacturing, we present descriptive evidence in Figure 1 that licensing, and associated support, increased domestic mask manufacturing and decreased mask prices. To implement this analysis, we construct a time series of domestic and border prices of masks in Rwanda, and compare to total turnover by domestic mask importers and manufacturers; details on the construction of these time series are in Appendix A.4.

First, large increases in both domestic prices and turnover of masks followed mask mandates in healthcare settings on March 14, 2020 and in all public settings on April 19, 2020. We interpret these policies as generating a large increase in demand for masks, which would increase both prices and quantities in the presence of an upward-sloping supply of masks.

Second, domestic mask prices began to fall toward pre-COVID-19 levels starting in May, 2020, coinciding with the peak of domestic manufacturing of masks that followed initial licensing of manufacturers on April 17. This coincidence provides suggestive evidence that domestic manufacturing decreased mask prices, but is insufficient to establish causality—alternative explanations that could have caused the observed decreases in the price of masks include increases in mask imports or decreases in demand for masks due to the reuse of masks. In Section 2, we therefore isolate exogenous variation in exposure to mask manufacturing across sub-Districts to estimate the impacts of mask manufacturing on purchases of domestically manufactured masks, mask prices, and COVID-19 infections.

2 Impacts of domestic mask manufacturing

2.1 Empirical strategy

2.1.1 Construction of mask manufacturing exposure

To estimate the impacts of access to mask manufacturing on purchases of domestically manufactured masks, mask prices, and COVID-19 infections, we begin with the following observation: purchases of manufactured masks at "destination" sub-Districts depend on their exposure through trade networks to mask manufacturers at "origin" sub-Districts.

We characterize origin sub-Districts o by their mask manufacturing intensity, which we define to be the fraction of their total sales that are manufactured masks. Let $X_{od,t}$ and $X^M_{od,t}$ denote expenditures, and expenditures on manufactured masks, respectively, by destination sub-District d from origin sub-District o in month t. We define

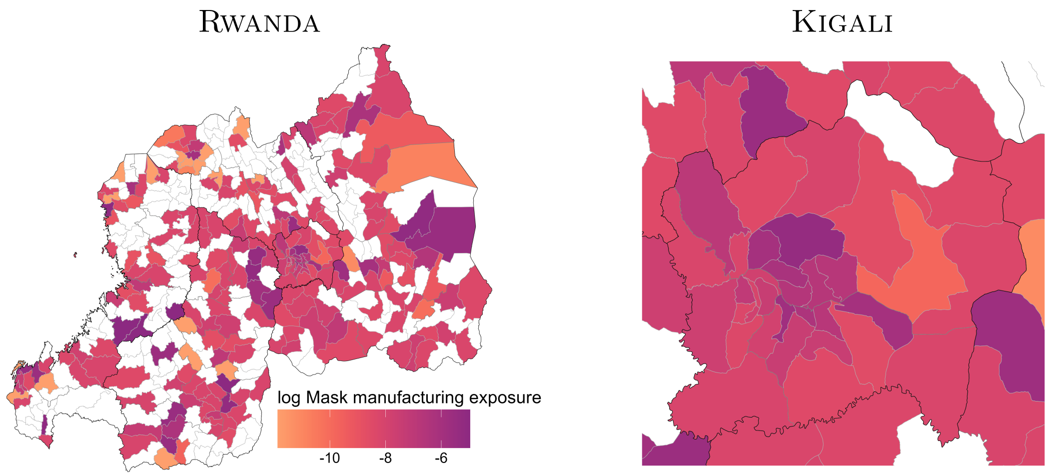
$$\text{Mask manufacturing intensity}_o \equiv \frac{\sum_{d,t} X^M_{od,t}}{\sum_{d,t} X_{od,t}} \tag{1}$$

We leverage our definition of mask manufacturing intensity to construct exposure, through trade networks, of destination sub-Districts to mask manufacturing. We construct a shift-share (Bartik, 1991) measure that eliminates potential dependence of exposure on demand for manufactured masks in two steps. First, we use pre-licensing purchases of textiles *excluding masks* by destination sub-District d from origin sub-District o, $X^T_{od,0}$, to characterize trade networks. Second, we measure the mask manufacturing intensity of origin o excluding the purchases of destination sub-District d.[3] We then define

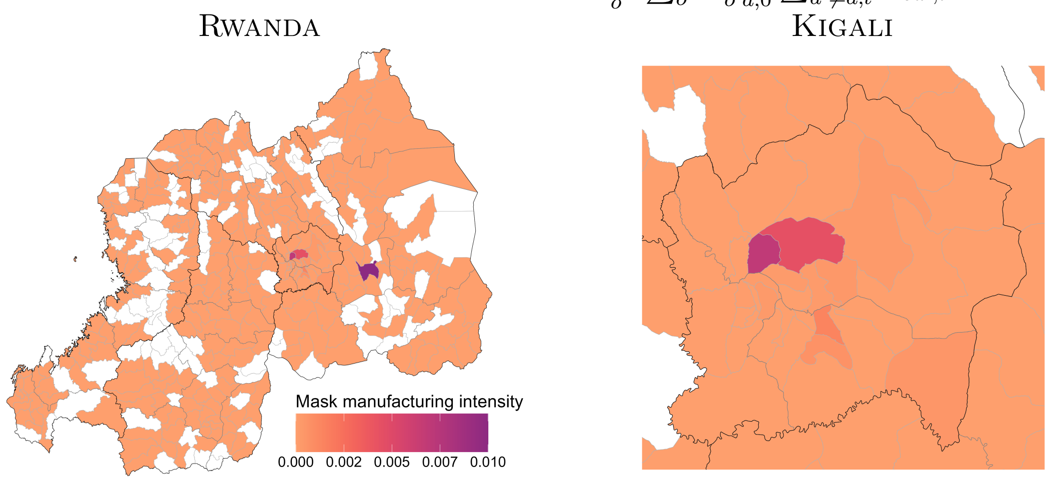
$$\text{Mask manufacturing exposure}_d \equiv \sum_o \underbrace{\frac{X^T_{od,0}}{\sum_{o'} X^T_{o'd,0}}}_{\substack{\text{pre-licensing non-mask}\\ \text{textile share}}} \underbrace{\frac{\sum_{d'\neq d,t} X^M_{od',t}}{\sum_{d'\neq d,t} X_{od',t}}}_{\substack{\text{leave-out mask}\\ \text{manufacturing intensity}}} \tag{2}$$

We plot variation in log mask manufacturing exposure across sub-Districts in Figure 2a, and for comparison plot variation in mask manufacturing intensity in Figure 2b.

[3]The exclusion of destination sub-District d's mask purchases follows a suggestion by Goldsmith-Pinkham et al. (2020), and in Table A5 we show this does not affect our results.



(a) $\log \text{Mask manufacturing exposure}_d \equiv \log \sum_o \frac{X^T_{od,0}}{\sum_{o'} X^T_{o'd,0}} \frac{\sum_{d' \neq d,t} X^M_{od',t}}{\sum_{d' \neq d,t} X_{od',t}}$



(b) $\text{Mask manufacturing intensity}_o \equiv \frac{\sum_{d,t} X^M_{od,t}}{\sum_{d,t} X_{od,t}}$

Figure 2: Mask manufacturing exposure and intensity vary substantially across sub-Districts

Notes: Figure 2a plots variation in mask manufacturing exposure across sub-Districts. Figure 2b plots variation in mask manufacturing intensity across sub-Districts. The left side in each panel plots variation across Rwanda, while the right side in each panel plots variation within Kigali City Province.

2.1.2 Estimating the impacts of mask manufacturing exposure

We estimate the impacts of exposure to licensed domestic mask manufacturing on mask purchases, mask prices, and the spread of COVID-19 using an event-study design. For outcome y_{dt} measured in sub-District d in month t, we estimate the following two-way fixed effects specification:

$$y_{dt} = \beta_t \log \text{Mask manufacturing exposure}_d + X_d' \delta_t + \theta_d + \gamma_t + \epsilon_{dt} \tag{3}$$

θ_d and γ_t are a set of sub-District fixed effects and month fixed effects, respectively. $X_d' \delta_t$ allows time-varying coefficients on sub-District characteristics that may be correlated with both mask manufacturing exposure and time trends (Duflo, 2001). Our coefficients of interest are β_t, the impact of log mask manufacturing exposure in month t. We use March 2020, one month prior to the initial licensing of textile manufacturers to produce multi-layer masks, as the reference month. Coefficients β_t should therefore be interpreted as impacts on changes in outcomes relative to March 2020. For inference, we cluster standard errors at the sub-District-level, the level at which mask manufacturing exposure varies.

To compactly present our estimates, we estimate two variants of Equation 3. First, we estimate a difference-in-difference specification, in which we instead interact log mask manufacturing exposure with a post-licensing indicator. This specification estimates the impact of mask manufacturing exposure on average outcomes from April 2020 through April 2021, relative to average outcomes from November 2019 through March 2020. Second, we instead interact log mask manufacturing exposure with separate post-licensing indicators for pre-national quality standards (April 2020 through June 2020) and post-national quality standards (July 2020 through April 2021), estimating impacts separately for these two periods.

Our estimates of the impacts of mask manufacturing exposure will be unbiased if mask manufacturing exposure is exogenous to other determinants of changes in the availability and prices of masks, and the spread of COVID-19. For this exogeneity to hold, we assume that destination sub-Districts that disproportionately source other textiles from high mask manufacturing intensity origin sub-Districts would have had similar changes to other sub-Districts in demand or supply of certified masks and COVID-19 infections absent licensed domestic mask manufacturing (Goldsmith-Pinkham et al., 2020). For this assumption to hold, it is particularly important that we have excluded masks when constructing our measures of other textile sourcing, to eliminate their dependence on mask demand. In contrast, it is unlikely that idiosyncratic shocks to demand or supply of masks will be correlated with the sourcing of non-mask textiles (predominantly clothing).

We have three primary outcomes of interest in Equation 3: log buyer prices of masks, per adult mask purchased quantities from manufacturers, and COVID-19 infections. We adapt Equation 3 or its estimation for two of these outcomes. First, when log buyer prices of masks are the outcome of interest, we do not aggregate to the destination sub-District-month, as changes in aggregated prices would include changes in the firm-product composition of purchased masks. We instead construct log buyer prices as mean log prices at the destination sub-District-by-month-by-firm-product level, and include firm-product fixed effects in Equation 3 to control for any unobservable mask characteristics that might influence price, such as style or material. Second, when COVID-19 infections are the outcome of interest, we instead use the number of purchases of paracetamol, a commonly recommended fever medicine, as a proxy for COVID-19 infections.[4] To produce estimates that are readily comparable to existing work, we estimate impacts on changes in the log number of purchases of paracetamol. As the number of purchases of paracetamol is frequently 0 in a given sub-District, we estimate Equation 3 using Poisson pseudo maximum likelihood (Wooldridge, 1999; Silva & Tenreyro, 2006).

2.1.3 Specification tests

We test the robustness of our assumption of the exogeneity of mask manufacturing exposure in three ways, adapting suggestions from Goldsmith-Pinkham et al. (2020) for difference-in-differences with shift-share instruments to our event-study design; the results of all three tests corroborate the exogeneity of exposure to policy-induced mask manufacturing. First, in Section 2.2 we show log mask manufacturing exposure is weakly correlated with exogenous sub-District characteristics, and in Section 2.3 we show our results are robust to including or excluding any sub-District characteristics

[4] We use purchases of paracetamol as a proxy because we do not have data on sub-District COVID-19 infections as COVID-19 testing in Rwanda did not become widespread until August 2020. In Appendix Table A4, we show that increased purchases of paracetamol are associated with increased COVID-19 infections at the District-level. As COVID-19 infections are not the sole cause of fever, and therefore of purchases of paracetamol, we discuss how this impacts the interpretation of our magnitudes in Appendix C.

X_d correlated with mask manufacturing exposure from Equation 3. Second, in Section 2.3 we show log mask manufacturing exposure is uncorrelated with trends in outcomes prior to licensing. Third, we show in Section 2.3 that replacing our measure of leave-out mask manufacturing intensity with its normalization by Province-specific mean leave-out mask manufacturing intensity does not affect our results; this normalization changes the weights placed on destination sub-Districts' exogenous non-mask textile purchase shares across origins (Goldsmith-Pinkham et al., 2020).

Equation 3 does not feature a staggered design, and therefore is not subject to recent criticisms of two-way fixed effects specifications with a staggered rollout (e.g., de Chaisemartin & D'Haultfœuille, 2020). However, it is similar to specifications analyzed in recent work that demonstrates the parallel trends assumption is insufficient for identification in difference-in-difference designs with continuous treatment (in our context, log mask manufacturing exposure) when treatment effect heterogeneity is correlated with treatment (Callaway et al., 2024). Here, a stronger exogeneity assumption is sufficient for identification, and we test this assumption in Section 2.2. A similar issue emerges when controls are interacted with time fixed effects in a two-way fixed effects specification, even when treatment is binary (Borusyak et al., 2024). In Section 2.3, we show that our results are robust to the inclusion or exclusion of controls interacted with time fixed effects.

Equation 3 jointly tests for parallel trends pre-licensing and estimates impacts post-licensing, which can introduce bias from pre-testing (Roth, 2022); in Figure A2 we follow Borusyak et al. (2021) and show our event study estimates are robust to an approach that eliminates this bias.

2.2 Balance

In Columns 1 and 2 of Table 1, we begin by estimating the association between sub-District characteristics and mask manufacturing intensity; we should not expect mask manufacturing intensity to be exogenous, as sub-Districts for which sales of masks by licensed textile manufacturers comprise a large share of turnover are likely to be very different from sub-Districts which do not have any licensed textile manufacturers. Consistent with this, we find that high mask manufacturing sub-Districts have higher turnover and purchase more inputs, and are more likely to have a textile manufacturer. Omnibus F-tests strongly reject the joint null of no association between mask manufacturing intensity and sub-District characteristics.

In contrast, in Columns 3 through 6 of Table 1, we show that mask manufacturing exposure is more weakly correlated with destination sub-District characteristics. This result holds across specifications that do and do not control for Province fixed effects, and specifications that do and do not replace leave-out mask manufacturing intensity with its normalization by Province-specific mean leave-out mask manufacturing intensity. We do consistently find statistically significant differences at the 10% level across high and low mask manufacturing exposure sub-Districts for four variables: high mask manufacturing exposure sub-Districts have more input purchases, greater population density, are more educated, and have lower employment rates. In Section 2.3, we therefore show that our results are robust to including or excluding as controls these four sub-District characteristics interacted with time fixed effects.

Table 1: Mask manufacturing exposure is weakly correlated with sub-District characteristics

	Mask manufacturing intensity		log Mask manufacturing exposure			
	(1)	(2)	(3)	(4)	(5)	(6)
log turnover	23.69	19.93	0.29	0.19	0.34	0.33
	(13.84)	(6.80)	(0.19)	(0.17)	(0.31)	(0.25)
	[0.09]	[0.004]	[0.14]	[0.25]	[0.28]	[0.18]
log purchases	28.73	26.48	0.28	0.23	0.35	0.33
	(10.35)	(3.69)	(0.07)	(0.06)	(0.12)	(0.09)
	[0.01]	[0.00]	[0.000]	[0.000]	[0.005]	[0.000]
log population density	−0.38	0.78	0.07	0.01	0.17	0.10
	(5.19)	(1.66)	(0.04)	(0.03)	(0.07)	(0.05)
	[0.95]	[0.65]	[0.07]	[0.79]	[0.02]	[0.07]
% completed secondary school	27.81	1.68	2.02	1.14	2.62	2.04
	(69.11)	(14.12)	(0.47)	(0.30)	(0.88)	(0.57)
	[0.69]	[0.91]	[0.000]	[0.000]	[0.003]	[0.000]
% employed	−19.19	−10.29	−0.40	−0.28	−0.49	−0.48
	(21.15)	(13.36)	(0.12)	(0.10)	(0.21)	(0.15)
	[0.37]	[0.45]	[0.002]	[0.01]	[0.02]	[0.002]
any textile manufacturer	11.83	6.91	0.04	−0.02	0.05	0.03
	(2.02)	(3.78)	(0.02)	(0.03)	(0.03)	(0.05)
	[0.00]	[0.07]	[0.02]	[0.48]	[0.12]	[0.50]
log population	−0.66	−8.77	0.02	0.04	−0.01	0.07
	(1.50)	(5.78)	(0.01)	(0.03)	(0.02)	(0.05)
	[0.67]	[0.13]	[0.27]	[0.11]	[0.57]	[0.21]
Province FE		X		X		X
Normalized intensity					X	X
# clusters (sub-districts)	317	317	239	239	239	239
Omnibus F	289.16	44.96	4.02	4.39	2.07	3.32
	[0.000]	[0.000]	[0.000]	[0.000]	[0.05]	[0.002]

Notes: Columns 1 and 2 report coefficients from regressions of sub-District characteristics on mask manufacturing intensity, while Columns 3 through 6 report coefficients from regressions of sub-District characteristics on log Mask manufacturing exposure. Robust standard errors are clustered at the sub-District level are reported in parentheses, and p-values are reported in brackets. Columns 2, 4, and 6 control for Province fixed effects, while Columns 5 and 6 and normalize mask manufacturing intensity by province average mask manufacturing intensity before constructing mask manufacturing exposure. In 35 sub-Districts log turnover is not defined where other sub-District characteristics are: we drop these sub-Districts in regressions of log turnover on intensity and exposure.

2.3 Results

2.3.1 Impacts of mask manufacturing exposure

We now present our results on the impact of mask manufacturing exposure on mask prices, purchases of masks from manufacturers, and COVID-19 infections. Table 2 reports estimates of these impacts from Equation 3; we focus our discussion on estimates from Columns 1, 3, and 5 from our most parsimonious specification without controls, as estimates are quantitatively and qualitatively similar when we include controls. Similarly, Figure 3 presents month-by-month event study coefficients from the specification without controls. All impacts are relative to March 2020, the month before the licensing of domestic textile manufacturers to produce high-quality masks was announced.

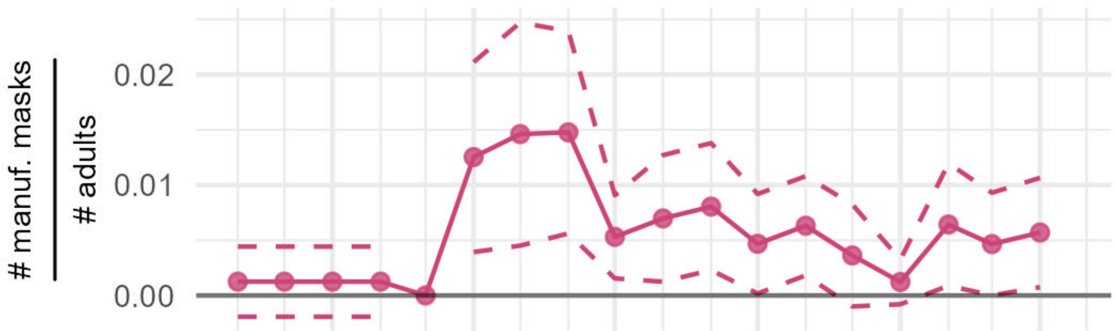
Table 2: Mask manufacturing exposure increases purchases of masks from manufacturers, decreases mask prices, and reduces COVID-19 infections

	Dependent variable					
	$\frac{\text{\# manuf. masks}}{\text{\# adults}}$		log mask price		# paracet. purch.	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Difference-in-Differences						
log Mask manufacturing exposure$_d$ $\times$Post$_t$	0.006	0.004	-0.052	-0.096	-0.268	-0.247
	(0.002)	(0.002)	(0.031)	(0.035)	(0.140)	(0.135)
	[0.001]	[0.108]	[0.096]	[0.006]	[0.056]	[0.067]
Panel B: Universal quality standards						
log Mask manufacturing exposure$_d$	0.013	0.009	-0.075	-0.112	-0.202	-0.120
$\times$Post$_t$	(0.004)	(0.006)	(0.029)	(0.034)	(0.115)	(0.101)
$\times$Pre-universal quality standards$_t$	[0.001]	[0.094]	[0.011]	[0.001]	[0.078]	[0.237]
log Mask manufacturing exposure$_d$	0.004	0.002	-0.042	-0.088	-0.280	-0.273
$\times$Post$_t$	(0.002)	(0.002)	(0.033)	(0.037)	(0.151)	(0.149)
$\times$Post-universal quality standards$_t$	[0.007]	[0.350]	[0.213]	[0.018]	[0.063]	[0.067]
Estimation method	OLS	OLS	OLS	OLS	Poisson	Poisson
Firm-product FE			X	X		
Destination sub-District FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Normalized intensity		X		X		X
Controls $\times$ Month FE		X		X		X
# observations	4,302	4,302	9,748	9,748	2,502	2,502
# clusters (sub-Districts)	239	239	239	239	139	139

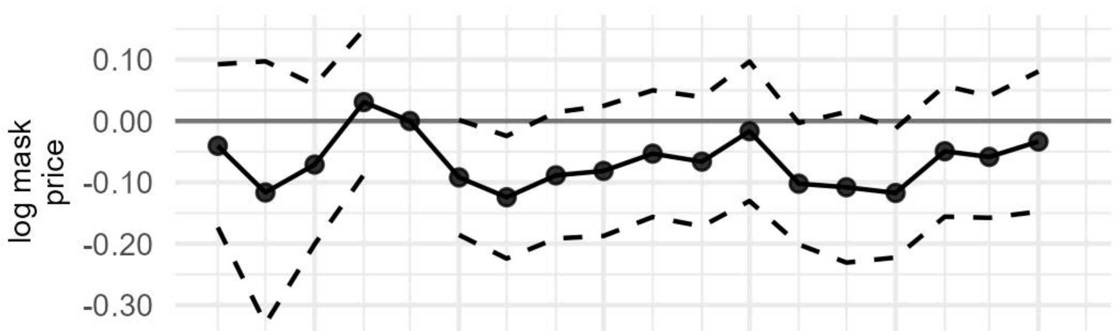
Notes: Columns 1 through 6 report coefficients on mask manufacturing exposure interacted with month fixed effects from estimates of Equation 3. Robust standard errors are clustered at the sub-District level and p-values are reported in brackets. All columns include destination sub-District fixed effects and month fixed effects. Columns 1 and 2 include firm-product fixed effects, while Columns 5 and 6 estimate coefficients using Poisson pseudo maximum likelihood. Columns 2, 4, and 6 include month fixed effects interacted with controls for Province fixed effects, log population density, log purchases in EBM, the employment rate and secondary school completion and normalize mask manufacturing intensity by province average mask manufacturing intensity before constructing mask manufacturing exposure.

Figure 3: Mask manufacturing exposure increases purchases of masks from manufacturers, decreases mask prices, and reduces COVID-19 infections

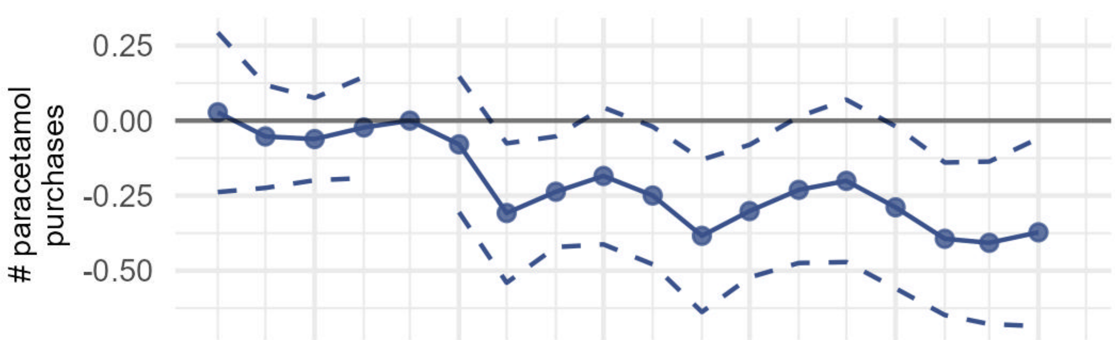
(a) Quantity of masks purchased from manufacturers per adult



(b) log mask price



(c) log purchases of paracetamol



Notes: Figure 3 presents monthly event study estimates of Equation 3. Confidence intervals use robust standard errors are clustered at the sub-District level and presented at 5% significance. All figures include destination sub-District fixed effects and month fixed effects. Figure 3b includes firm-product fixed effects, while Figure 3c presents estimated coefficients using Poisson pseudo maximum likelihood.

First, exposure to mask manufacturing causes persistent decreases in the price of masks through greater access to mask markets. A one standard deviation increase in mask manufacturing exposure reduced mask prices by 7.5%. This estimate represents a lower bound in that it does not account for across sub-District general equilibrium effects through markets for non-manufactured masks. We take two approaches to interpreting the magnitude of this effect. First, April 2020 mask prices were 197% higher in Rwanda than in January, associated with the large increase in demand for masks during the COVID-19 pandemic, while by June, prices had fallen 30% below April levels. The impacts of mask manufacturing exposure, relative to the April-to-June decrease in prices, suggest a substantial share of this price decrease is explained by domestic mask manufacturing. Second, as mask manufacturing exposure is constructed from differences across sub-Districts in non-mask textile trade flows, we interpret these impacts as being driven by persistent differences in costs of trade between sub-Districts. Building on this interpretation, we combine our estimated impacts of mask manufacturing exposure on prices with estimates from a gravity regression of log textile trade flows on log distance in Table A3; the resulting back-of-envelope calculation implies that a 10% decrease in distance to mask manufacturing at average mask manufacturing exposure causes a 0.3% decrease in mask prices.[5]

Second, the persistent decrease in mask prices caused by exposure to mask manufacturing caused large, temporary increases in purchased mask quantities from manufacturers prior to the enforcement of quality standards nationally. As shown in Figure 3, impacts on purchased mask quantities from manufacturers are large and significant from April through June, but fade significantly thereafter; our estimates in Table 2 imply that impacts post-June are 70% smaller than impacts April-through-June. We argue that our results in the initial months reflect substitution away from informal non-certified masks into domestically manufactured certified masks in sub-Districts with high mask manufacturing exposure, while the declining impacts are driven by this same substitution occurring in sub-Districts with low mask manufacturing exposure due to the June gazetting of quality standards for masks sold in Rwanda. Quality standards were already met by masks produced by licensed manufacturers, as we discuss in Section 1.2. As a result, these standards primarily targeted the infor-

[5]For comparison, Donaldson (2018) estimates a 10% decrease in distance to the source of salt causes a 0.9%–1.7% price decrease in salt prices in India; that our estimate is somewhat smaller is likely explained by the shorter distances in our context.

mal sale of non-certified masks, while mask purchases in our data are of domestically manufactured and imported masks, which likely already met these standards.[6] In summary, the introduction of a ban on a substitute product (informal non-certified masks) decreased the elasticity of demand for domestically manufactured masks, and particularly so when coupled with strictly enforced mask mandates, and this decreased the quantity response of certified manufactured masks to the persistent price decrease caused by exposure to mask manufacturing.

To interpret magnitudes of the impacts of mask manufacturing exposure on quantities, we calculate that our pre-universal quality standards estimate of the impacts on prices and quantities imply a price elasticity of demand of -2.1.[7] This estimated elasticity is larger than comparable estimates from Berry et al. (2020) for water filters, consistent with the availability of a close substitute for certified manufactured masks (non-certified masks) in these early months.[8]

Third, licensed domestic mask manufacturing slowed the spread of COVID-19 at early stages of the pandemic; however, trade frictions reduced access to certified masks in less exposed sub-Districts, temporarily increasing infection growth and persistently increasing the level of infections in less exposed sub-Districts. While we only observe impacts on purchases of paracetamol, we assume they are a valid proxy for sub-District COVID-19 infections. We estimate their association using much more aggregated District-level data on COVID-19 infections in Appendix Table A4, and find that a 1% increase in purchases of paracetamol is associated with a 0.3% increase in COVID-19 infections; we scale impacts on purchases of paracetamol by this coefficient to recover impacts on COVID-19 infections. To interpret our point estimates, we scale impacts on COVID-19 infections by the standard deviation of mask manufacturing exposure—our estimates imply that, before the introduction of universal quality standards, a one standard deviation increase in mask manufacturing exposure reduced the monthly growth rate of COVID-19 infections nationally by 2.9%.

[6] As we expect both domestically manufactured and imported masks are high quality, we might expect both types to impact the spread of COVID-19.

[7] To calculate this elasticity, we divide the impact on mask quantities from manufacturers as a share of the adult population by its average value in the April-through-June period before universal quality standards (0.081), and divide this by impacts on log buyer price. In results available upon request, we recover somewhat larger elasticities when we instead use Poisson pseudo maximum likelihood estimates of impacts on expected log mask quantities from manufacturers per adult.

[8] Berry et al. (2020) find elasticities of between 0 and 4 over a range of prices, but elasticities below 1 closer to break-even prices.

Similar to estimates of price impacts, this estimate reflects a lower bound, because of both across-sub-District transmission of COVID-19 and any across sub-District general equilibrium price effects. While impacts on COVID-19 infections grew steadily before the introduction of universal quality standards in June, they remain constant after—this implies that, while the impacts of domestic mask manufacturing on infection growth persist through June, they dissipate after. This however leaves persistent impacts on the level of COVID-19 infections.

2.3.2 Interpreting impacts of mask manufacturing exposure on infections

To explain the dynamics of impacts on COVID-19 infections, we argue that the local impacts of exposure to mask manufacturing that we document are mediated by substitution away from informally produced masks toward formally manufactured masks, rather than by increases in the use of masks. As discussed in Section 1.2, Rwanda had strict enforcement of mask mandates and high compliance starting April 19, suggesting that we should not expect there to be differences in mask use between sub-Districts with high and low exposure to licensed mask manufacturing; there may instead be differences in the types of masks used (and, specifically, in their quality).[9] While we do not directly observe the quality of informally manufactured masks in our data, the dynamics of these impacts lend support to quality as the main mechanism driving a wedge in COVID-19 infections across high- and low-exposure sub-Districts. We use the fact that, starting in June, national standards for mask quality (which already applied to certified manufacturers) were expanded to non-licensed manufacturers, shutting down the informal sales of masks, while licensing was extended to all formal garment manufacturers. Should quality be the main mechanism underlying our results, we should then see the impacts of mask manufacturing exposure on both manufactured mask purchases and COVID-19 infection growth fade over time. This is exactly what we observe.

The implied impacts of certified mask use on COVID-19 infections, based on our estimates, are consistent with empirical estimates of the impacts of high-quality masks from other contexts. We calculate impacts of certified mask use by dividing our pre-universal quality standards impacts on monthly growth in COVID-19 infections by our pre-universal quality standards impacts on mask purchases from licensed manu-

[9] According to the Innovations for Poverty Action RECOVR survey, 95% of households always wore a mask when they went out in Public.

facturers per adult. As mask mandates were strictly enforced, we interpret this scaled estimate as the effect of shifting a sub-District from limited use of certified masks (not purchasing formally manufactured masks) to universal use of certified masks (exclusively purchasing formally manufactured masks) at the early stages of the pandemic. We find that universal certified mask use reduces monthly infection growth by 53%. In Appendix C, we calculate estimates of closely related parameters from existing work; mask mandates for employees in public-facing businesses in the United States reduce monthly case growth by 35% (Chernozhukov et al., 2021), while surgical mask use reduces monthly infection growth by 18% in rural Bangladesh (Abaluck et al., 2021). Both estimates are statistically indistinguishable from ours; we note that the latter estimate is of impacts on villages (much smaller than sub-Districts) for which cross-village spillovers are likely to render estimates more conservative. That these three estimates are comparable is consistent with large effects of mask quality on COVID-19 transmission, in line with evidence from the lab (Konda et al., 2020) and from the field (Abaluck et al., 2021).

Our estimates of the impacts of mask manufacturing exposure do not account for any across sub-District general equilibrium effects; however, the shape of the supply of manufactured masks determines the effect of reductions in *trade costs* to mask manufacturing origins, conditional on licensing. When supply is fully elastic, these reductions in trade costs have no impacts on origin prices, and general equilibrium effects on manufactured mask prices are equal to partial equilibrium effects. In contrast, when supply is fully inelastic, these reductions in trade costs have no impacts on the production of manufactured masks; as a consequence, absent nonlinearities in the effects of manufactured mask purchases on COVID-19 infections, there are no aggregate impacts of reductions in domestic trade costs on manufactured mask purchases and, therefore, on COVID-19 infections.

3 Conclusion

In this paper, we show that an industrial policy aimed to increase the supply of high-quality masks slowed the spread of COVID-19 in Rwanda. We leverage the licensing of textile manufacturers to produce high-quality masks as a shock to mask production. To establish causality, we exploit the fact that sub-Districts are more likely to source masks from the same sub-Districts from which they source non-mask textiles, and yet non-mask textile sourcing does not predict pre-licensing changes in sub-District outcomes and is weakly associated with sub-District characteristics. Our results show licensing decreased mask prices and slowed the spread of COVID-19 in the early stages of the pandemic through increased access to formally manufactured masks. A cost-benefit calculation suggests averted hospitalization costs from estimated impacts on reduced COVID-19 infections were conservatively an order of magnitude larger than the fiscal costs of the VAT exemption for domestic mask manufacturing.[10]

We establish three key results: exogenous exposure to licensed mask manufacturing decreased mask prices, increased purchases of formally manufactured masks, and reduced COVID-19 infections. Although we do not directly observe mask quality, the dynamics of these impacts in the Rwandan context, where mask mandates were well enforced, suggest that increased quality of masks, rather than increased use, explains our results. Taken together, these results confirm the notion that constrained supply of high-quality masks accelerated the spread of COVID-19 at the early stages of the pandemic. While our results leverage sub-national variation in exposure to mask manufacturing, they suggest a similar role of access to masks in explaining international variation in the progression of the pandemic—i.e., there were not enough good masks.

[10]Details of this calculation are in Appendix D.

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A Data appendix

A.1 EBM data

We use the universe of EBM transactions made through EBM II as our original data from November 2019 through August 2020. EBM II is a software-based teller system introduced in 2018 as an alternative to traditional physical EBMs (EBM I).[A1] We restrict to data in November 2019 and later, because the number of active EBM II devices in November increased by 50% relative to October, as part of a large EBM II registration drive.[A2]

EBM is mandated for use by VAT taxpayers, described in Appendix A.3. Receipts issued by registered taxpayers are transmitted via an internet connection to RRA. In November 2019, EBM II recorded 81.8 billion RwF of value added, or 10.4% of GDP on 470,000 receipts.

Each EBM is identified by a unique Sales Data Controller (SDC) ID, and issues receipts which are digitally signed with a unique Sales Data Controller Receipt Signature (SDCS). A fictitious EBM receipt is depicted in Appendix Figure A1. Each receipt enumerates the transacted items, and records the prices at (and quantities in) which they were sold.

EBM II receipts include both a United Nations Standard Products and Services Code (UNSPSC) classification code and detailed item descriptions for each item. We refer to the item description as the product. Since each SDC is associated with a unique Taxpayer Identification Number (TIN), the seller is identified in all transactions. If the buyer provides their unique TIN for the transaction, both the buyer and the seller are identified by the receipt.[A3] Receipts are timestamped with the date and time of issue.[A4]

[A1]EBMs, or Electronic Billing Machines, are no longer exclusively physical machines. For this reason, Electronic Invoicing Systems (EIS) nomenclature is used as an umbrella term for both physical and digital/software-based receipt generating systems. To align with the colloquial usage in Rwanda, in this Appendix we refer to any official receipt generating system as EBM, and delineate versions when referring to any specific form of EBM (EBM I, EBM II). In the body of the paper, for parsimony we refer to EBM II as EBM, both because we do not use EBM I data for our analysis and also because of the relatively broad coverage of EBM II.

[A2]Although EBM I offers more coverage before November 2019, these receipts are not comprehensively stored in a machine readable format.

[A3]Since firms require receipts to claim input tax credits, we consider unidentified buyers as final consumers.

[A4]While transmission of the receipt to RRA can be delayed, either if software is malfunctioning

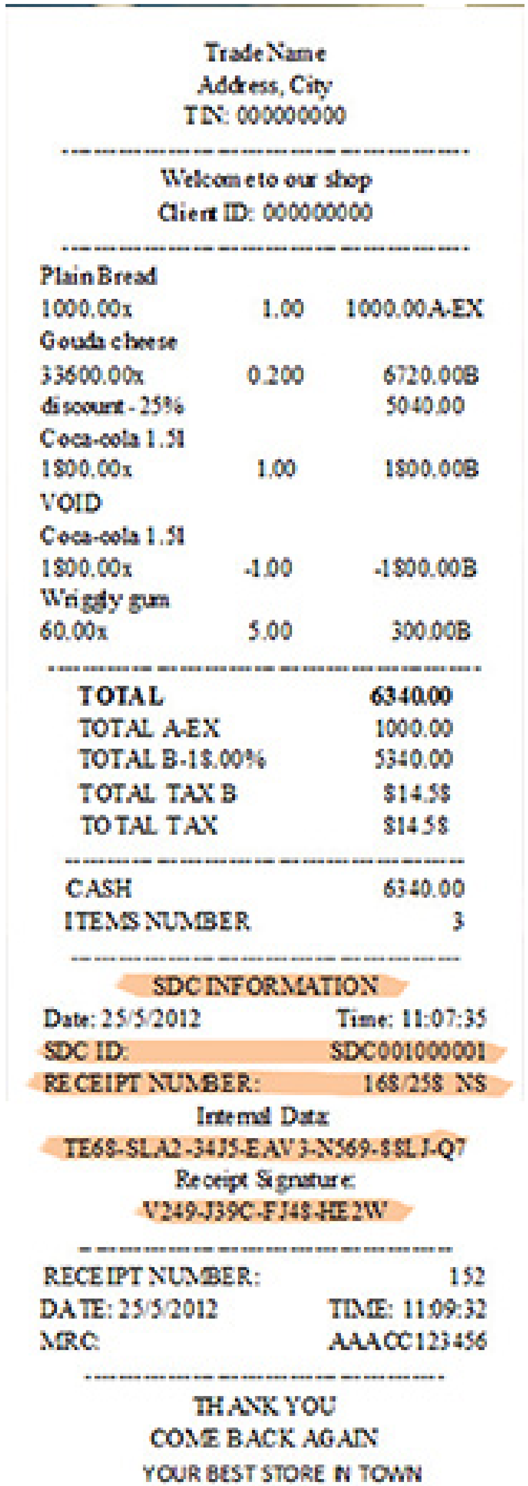
While an SDC is associated with one TIN, a firm may have multiple EBMs. Since we do not observe the location of each SDC, we assume that the EBM is located in the same sub-District as the firm, which we identify using firm registration data (see Appendix A.3 for a description of firm registration data). In November 2019, 95.5% of EBM II taxpayers reported having only one EBM II device.

Since most EBM receipts identify both a buyer and a seller, we are able to map mask supply chains from the sub-District of the seller to the sub-District of the buyer. We retain a receipt-by-firm-product dataset (aggregated to a buyer sub-District-by-firm-product-by-month dataset for our main analysis) to study mask prices and construct a balanced buyer sub-District-by-month dataset to study purchases of masks and paracetamol across sub-Districts.

The primary purpose of EBM is to support the self-enforcing design of the VAT (Pomeranz, 2015). Through the creation of a paper trail, EBM increases the information with which RRA can validate declarations and undertake audits. In Rwanda, VAT input credits must be supported by EBM receipts, creating an incentive for the buyer to both request and associate their TIN with a purchase receipt.

or if the internet connection is unstable, RRA estimates 98% of total receipts due to be declared are transmitted within two weeks.

Figure A1: A fictitious EBM receipt



Trade Name
Address, City
TIN: 000000000

Welcome to our shop
Client ID: 000000000

Plain Bread		
1000.00x	1.00	1000.00A-EX
Gouda cheese		
33600.00x	0.200	6720.00B
discount - 25%		5040.00
Coca-cola 1.5l		
1800.00x	1.00	1800.00B
VOID		
Coca-cola 1.5l		
1800.00x	-1.00	-1800.00B
Wriggly gum		
60.00x	5.00	300.00B

TOTAL	**6340.00**
TOTAL A-EX	1000.00
TOTAL B-18.00%	5340.00
TOTAL TAX B	814.58
TOTAL TAX	814.58

CASH	6340.00
ITEMS NUMBER	3

SDC INFORMATION

Date: 25/5/2012	Time: 11:07:35
SDC ID:	SDC001000001
RECEIPT NUMBER:	168/258 NS

Internal Data:
TE68-SLA2-34J5-EAV3-N569-88LJ-Q7
Receipt Signature:
V249-J39C-FJ48-HE2W

RECEIPT NUMBER:	152
DATE: 25/5/2012	TIME: 11:09:32
MRC:	AAACC123456

THANK YOU
COME BACK AGAIN
YOUR BEST STORE IN TOWN

A.1.1 EBM data construction

Our analysis of the EBM data is built on a dataset of prices and quantities at the buyer sub-District-by-firm-product-by-month level. We construct the following outcomes from this data:

Product description Each item in a receipt is accompanied by a free-fill description entered by the firm (e.g., "Coca-cola 1.5l"). Firms enter these descriptions to EBM II software when they receive new stock. EBM II subsequently prints the description of each item at the point of sale.

Value and quantity To account for cancellations in the data, we aggregate over values and quantities of receipt items on the same receipt, with the same item description, the same price and the same product code. For the example in Figure A1 this creates a quantity and value of the third and fourth item will be 1 + -1 = 0 and 1800 + -1800 = 0, respectively. We remove products from our dataset which were voided or cancelled. We also remove two taxpayers from our dataset which record implausibly large changes in turnover.

Price We take the following steps to improve measurement of prices. First, as described in Section 2.1.2, we employ firm-product fixed effects in all analysis of prices to ensure that we are appropriately comparing mask prices adjusting for quality differences across firm-products. Second, we note that the units in which retailers report a sale of masks within firm-product are sometimes imperfectly measured in the data. We therefore winsorize prices within firm-product at the 5th and 95th percentiles.

We identify products using string descriptions. To identify masks and paracetamol, we string match masks and paracetamol, respectively, in English, French, and Kinyarwanda (e.g., mask, masque, agapfukamunwa) in product descriptions. We subsequently remove products from this data, which satisfy the matching algorithm, but are not face masks. This includes, for example, packaging for masks ("Mask Envelope") or masks for nebulizers.

Product UNSPSC codes In order to determine the tax status of a product, firms classify their inventory using United Nations Standard Products and Services Code

(UNSPSC) codes. We identify textile products (a product grouping) using UNSPSC codes 601058, 5310 and 2312. We ensure that the string descriptions conform to the UNSPSC product descriptions for each code.

A.1.2 EBM descriptive statistics

Table A1: Masks in EBM

	Manufacturer (1)	Retailer/Trader (2)	Importer (3)
# sub-Districts	26	108	44
# mask purchasing sub-Districts	26	107	44
# mask selling sub-Districts	15	70	16
# firms	519	2,286	1,577
# of mask purchasing firms	504	1,987	1,552
# of mask selling firms	25	502	65
# receipts	1,663	69,990	15,804
# of mask sales	1,746	71,045	16,093
# of masks	1,346,059	2,684,475	684,446
Mask sales, RwF	643,380,638	1,075,685,848	1,499,129,971

Notes: Summary statistics, either counts or total values, on mask sales in EBM during our study period are reported in this table. Column 1 reports statistics on sales by manufacturers, Column 2 reports statistics on sales by non-manufacturers excluding mask importers, and Column 3 reports statistics on sales by non-manufacturer mask importers.

Table A2: Mask supply chains in EBM

	Sales to (destination) sub-District (1)	Purchases from (origin) sub-District (2)
sub-Districts	2.07 (2.23)	16.40 (20.29)
Firms	2.47 (3.45)	41.07 (58.15)
Receipts	14.99 (47.88)	118.93 (166.52)

Notes: Average counts on mask sales in EBM during our study period are reported in this table, with standard deviations in parentheses. Column 1 reports counts for sales to each destination sub-District (excluding destination sub-Districts with no purchases), while Column 2 reports counts for sales from each origin sub-District (excluding origin sub-Districts with no sales).

A.2 Customs data

To compare the local and global mask markets we complement domestic EBM II data with similarly granular international trade data. Customs data collected by RRA contains the universe of tax-registered importing firms based in Rwanda. Importing firms are identified by the same Taxpayer Identification Number (TIN) which identifies a firm for domestic declarations (including VAT).

The data includes the imported value, weight, product unit, Harmonized System (HS) product codes, an import origin and a timestamp at the point of entry. In addition, two free-text string fields are populated with product descriptions by customs officers. We identify masks using a combination of HS product codes, and product string descriptions. Just as in EBM data, we exclude items outside the scope of our study (e.g., oxygen masks).

A.2.1 Customs data construction

Product descriptions At import, product descriptions are captured by RRA customs officers at the border. We identify imports exclusively containing masks using string descriptions. We subsequently remove products from customs data, which satisfy the matching algorithm, but are not face masks.

Price The most salient difference for our research, between customs and EBM data is that no natural price (per unit) variable exists in the international trade data. The data does include the total imported value, as measured by the Cost, Insurance, Freight (CIF), and several quantity variables including *product quantity* and Net Weight (KG). As discussed in Appendix A.1 units of quantity may vary. We use the import value and weight to construct a mask price per unit of weight for transaction r made at the firm-border post combination f in month t.

$$p^{\text{imp}}_{rft} = \frac{\text{CIF}_{rft}}{\text{KG}_{rft}}$$

We winsorize border prices at the 5th and 95th percentile.

A.3 Additional appendix data sources

Firm registration Firm registration data contains firm-level details including the ISIC sector classification, and the Province, District and sub-District in which the firm operates. This data is collected when the firm is formally registered at the Rwanda Development Board (RDB) and continuously monitored and updated by RRA.

Census

A.4 Time series of mask prices

To construct our time series of mask prices, we estimate the following equations to document changes in both domestic prices and border prices of masks in Rwanda during the COVID-19 pandemic. For both domestic and imported masks, we consider transactions from November 2019 through April 2021.

Domestic mask prices To account for the composition of domestic mask sales, we construct prices as mean log prices at the month-by-firm-product level. We let p_{ft} be the mean log price of firm-product f sold domestically in month t. We then estimate

$$\log p_{ft} = \sum_{t=\text{Nov 2019}, t\neq \text{Jan 2020}}^{\text{Apr 2021}} \tau_t + \alpha_f + \epsilon_{ft} \tag{A1}$$

where τ_t captures the change in log mask prices relative to January 2020, and α_f is a firm-product fixed effect that controls for any changes in the composition of masks sold domestically. We report standard errors clustered at the sub-District of the firm. As discussed in Section 1.2, starting April 2020 sales of domestically manufactured multi-layer masks grew relative to sales of imported medical masks.

Border mask prices For border prices, we similarly construct mean log prices per unit at the month-by-firm-border post level. Since unit mask prices are not naturally identified in the customs data, we prices per unit of weight, net of freight weight.[A5] Further, as we are unable to consistently identify products in the customs data, we use firm-border post fixed effects to account for changes in the composition of mask

[A5] See Appendix A.2 for additional details on this construction.

imports. We let p_{ft}^{imp} be the mean log price of imported masks in customs data for firm-border post f in month t.

$$\log p_{ft}^{\text{imp}} = \sum_{t=\text{Nov 2019}, t\neq \text{Jan 2020}}^{\text{Apr 2021}} \tau_t^{\text{imp}} + \alpha_f + \epsilon_{ft}^{\text{imp}} \tag{A2}$$

where τ_t^{imp} captures the change in log border prices of masks relative to January 2020, and α_f is a firm-border post fixed effect that controls for any changes in the composition of imported masks, assuming that variation in quality of imported masks and other unobservable determinants of price does not systematically vary over time within firm-border post. We report standard errors clustered at the firm level.

B Mask specifications and enforcement

B.1 Definition of mask quality

Guidelines for the manufacture of barrier masks were released by the Rwanda FDA[A6] and the Rwanda RSB[A7] on April 17 and April 24, respectively. The guidelines released by the RSB were gazetted in Rwandan Law in June 2020.[A8] The guidelines include references to:

- Performance: ISO specifications for penetration (for solid and liquid particles), air permanence (315-1265 μm/Pa s), and mass per unit area (120-250 g/m^2)
- Materials: cotton, viscose, polyester; multiple layers preferred
- Size: Four adult size specifications and three child specifications detailed (e.g., a small adult mask should measure 280-306 mm x 104-111 mm)
- Labelling: The manufacturer's name, the constituent material, recommended use period, handling instructions
- Packaging: Masks should be packaged to protect masks from contamination or damage

[A6] https://rwandafda.gov.rw/web/index.php?id=36
[A7] https://www.rsb.gov.rw/fileadmin/user_upload/files/pdf/new_stds/RS_433-2_2020.pdf
[A8] https://www.rsb.gov.rw/fileadmin/user_upload/files/pdf/new_stds/National_Standards_May_2020.pdf

B.2 Enforcement

Objective ISO testing metrics are outlined in the RSB's standards guidelines, which were gazetted into law in June 2020. Individual firms subsequently report subjecting their masks to quality checks. As a supporting anecdote, Chillington Rwanda (with support from the RSB) provided masks to the FDA for approval.[A9] As another, UFACO & VLISCO NL LTD reported inspections and compliance with the RSB standards before the masks were leave the factory gate.[A10]

In an interview on May 7 with Kigali Today, the Quality Control Division Manager at the RSB and the Director of Engineering Standards at the FDA discussed the issue of facemask quality at markets, and underscored their role as quality auditors; masks found to be non-compliant with standards were removed from markets, packaging should comply with the RSB standards:[A11]

> *After the policies were published* [April 17] *we started the inspection which makes me think that all face masks being manufactured now meet all the required standards*
> Director of Engineering Standards, FDA

C Comparison to existing estimates of impacts of masks on COVID-19 infections

Next, we scale our estimates of impacts of mask manufacturing exposure for comparability. We focus on our estimates without controls, and in particular of our estimate of the impacts of mask manufacturing exposure on average pre-universal quality standards sales of anti-fever medicine as a proxy for COVID-19 infections. We divide this estimate by 2 (as it averages over impacts 1, 2, and 3 months post-licensing) to recover impacts on monthly growth rates in infections – an increase in mask manufacturing exposure from 0 to 1 causes the monthly growth rate of COVID-19 infections (defined as the ratio of COVID-19 infections in the current month to COVID-19 infections in the previous month) to fall by 7.85%. We then take two approaches to scaling this

[A9] https://www.msdhub.org/blog/learning-story-spotlight-chillington-rwanda-pathways-for-adaptation-and-growth-responding-to-societies-and-customers-needs
[A10] http://expressnews.rw/are-face-masks-safe-with-health-standards-for-users/
[A11] https://www.youtube.com/watch?v=en8RdSauF2g

estimate. First, to evaluate the overall effect of mask manufacturing in Rwanda, we multiply our estimates by a standard deviation of log mask manufacturing exposure in our primary analysis sample (-8.13), and interpret this as the effect of setting mask manufacturing exposure equal to zero nationally. Alternatively, we divide our estimate by the pre-universal quality standards impact on per capita manufactured mask purchases (0.013) which we interpret as the effect of households exclusively sourcing masks from manufacturers. Applying the former, domestic mask manufacturing reduced the monthly growth rate of COVID-19 infections nationally by at least 2.9% before the introduction of universal quality standards. Applying the latter, shifting from no manufactured masks to complete adoption of manufactured masks causes the monthly growth rate of COVID-19 infections to fall by 53%.

We then compare this estimate to results from Chernozhukov et al. (2021) and Abaluck et al. (2021). Chernozhukov et al. (2021) find that mandating employees wear masks holding fixed behavior causes a 10% decrease in weekly case growth, which scales to a 35% decrease in monthly case growth; this is statistically indistinguishable from our estimate of the impacts of adoption of manufactured masks. Abaluck et al. (2021) find that promotion of masks led to a 29pp increase in mask wearing in public, which over 8 weeks was associated with an 11.2% reduction in symptomatic infections when surgical masks were provided. Scaling this estimate by the inverse of their estimated impacts on mask adoption yields an 19% decrease in monthly infection growth. While our estimates and theirs are not statistically different from one another, taking the point estimates at face value suggests larger impacts of masks on the spread of COVID-19 in the United States and in urban and peri-urban Rwanda than in rural Bangladesh; alternatively, the source of variation in mask policy in Bangladesh is at a much narrower geography (village) than in Rwanda and in the United States, suggesting across-village spillovers may reduce estimated impacts of masks on the spread of COVID-19 in Bangladesh.

D Cost-effectiveness

As described in Section 2.3, we estimate large decreases in COVID-19 infections caused by domestic mask manufacturing in Rwanda. In this section, we compare these impacts to available estimates of the fiscal costs of promoting domestic mask manufacturing in order; this provides the cost-effectiveness of promotion of domestic mask manufacturing as a policy to reduce COVID-19 infections.

First, to calculate the decrease in COVID-19 infections caused by domestic mask manufacturing in Rwanda, we multiply, in April 2020 through April 2021, monthly national new COVID-19 infections (from the Rwanda Biomedical Center) by our estimates of the monthly impacts of domestic mask manufacturing on COVID-19 infections from Section 2.3. As noted in Section 2.3.1, these estimates provide a lower bound on the impacts of domestic mask manufacturing on COVID-19 infections. Using this approach, we calculate domestic mask manufacturing averted 1,451 COVID-19 infections from April 2020 through April 2021.

Second, the fiscal costs of promoting domestic mask manufacturing are the sum of the costs of two policies described in Section 1.2: the VAT exemption for domestically manufactured masks, and administrative licensing costs. We calculate an upper bound on a fiscal costs of the VAT exemption as the value-added tax rate (18%) times the total turnover of exempted masks to final consumers from May through August. While we do not have data on licensing costs, we note that the small number of mask manufacturers suggests that the associated licensing and audit costs are likely to be small relative to the costs of the VAT exemption. Using this approach, we calculate a total cost of RwF 41 million (approximately $40,000) of the promotion of domestic mask manufacturing.

Third, we take the ratio of these two estimates, and find the cost of averting a COVID-19 infection through promotion of domestic mask manufacturing in Rwanda was 9,800 RwF/infection (approximately $9.5/infection). This is an order of magnitude smaller than estimates from Kenya of treating a COVID-19 infection, which range from $278 to $5,879 (Barasa & Kairu, 2020).

E Appendix tables

Table A3: Non-mask textile trade between sub-Districts is decreasing in distance

	Dependent variable:	
	Pre-licensing non-mask textile share	
	(1)	(2)
log distance	-0.379 (0.139) [0.006]	-0.281 (0.155) [0.069]
Estimation method	Poisson	Poisson
Intra-provincial trade dummy		X
Origin (sub-District) FE	X	X
Destination (sub-District) FE	X	X
# observations	16,904	16,904
# clusters (sub-Districts)	239	239

Notes: Columns 1 through 2 report coefficients on log distance between origin and destination sub-Districts. Standard errors are in parentheses, and p-values reported in brackets. Coefficients are estimated using Poisson pseudo maximum likelihood. All columns include origin sub-District fixed effects and destination sub-District fixed effects. Column 2 includes an indicator that origin and destination sub-Districts are in the same Province.

Table A4: Increases in number of paracetamol receipts are associated with increased COVID-19 cases

	Dependent variable:			
	Confirmed COVID-19 cases			
	(1)	(2)	(3)	(4)
log # paracetamol receipts	0.292 (0.058) [0.000]	0.292 (0.060) [0.000]	0.561 (0.120) [0.000]	0.459 (0.147) [0.002]
Estimation method	Poisson	Poisson	Poisson	Poisson
Month FE		X		X
Destination District FE			X	X
# observations	367	367	366	366
# clusters (Districts)	30	30	29	29

Notes: Columns 1 through 4 report coefficients on log number of paracetamol receipts. Standard errors are in parentheses, and p-values reported in brackets. Coefficients are estimated using Poisson pseudo maximum likelihood. Columns 2 and 4 include district fixed effects, Columns 3 and 4 include month fixed effects, and Column 4 includes month fixed effects interacted with controls for Province fixed effects, log population density, and log number of textile manufacturers.

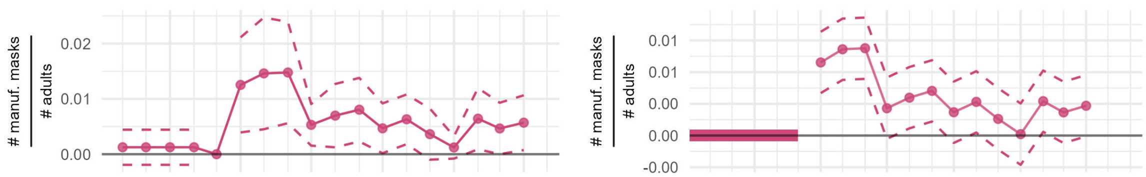
Table A5: Mask manufacturing exposure without jackknife increases purchases of masks from manufacturers, decreases mask prices, and reduces COVID-19 infections

	Dependent variable					
	# manuf. masks / # adults		log mask price		# paracet. purch.	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Difference-in-Differences						
log Mask manufacturing exposure$_d$ $\times$Post$_t$	0.007	0.001	-0.056	-0.095	-0.268	-0.231
	(0.002)	(0.001)	(0.030)	(0.033)	(0.140)	(0.128)
	[0.001]	[0.362]	[0.061]	[0.004]	[0.056]	[0.072]
Panel B: Universal quality standards						
log Mask manufacturing exposure$_d$ $\times$Post$_t$ $\times$Pre-universal quality standards$_t$	0.013	0.003	-0.079	-0.110	-0.193	-0.120
	(0.004)	(0.003)	(0.028)	(0.032)	(0.101)	(0.098)
	[0.001]	[0.313]	[0.005]	[0.001]	[0.056]	[0.221]
log Mask manufacturing exposure$_d$ $\times$Post$_t$ $\times$Post-universal quality standards$_t$	0.005	0.000	-0.046	-0.087	-0.235	-0.254
	(0.002)	(0.001)	(0.032)	(0.035)	(0.142)	(0.141)
	[0.006]	[0.564]	[0.157]	[0.014]	[0.098]	[0.072]
Estimation method	OLS	OLS	OLS	OLS	Poisson	Poisson
Firm-product FE			X	X		
Destination sub-District FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Normalized intensity		X		X		X
Controls × Month FE		X		X		X
# observations	4,302	4,302	9,748	9,748	2,502	2,502
# clusters (sub-Districts)	239	239	239	239	139	139

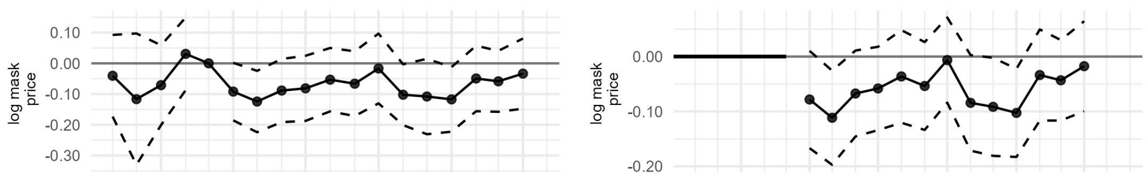
Notes: Columns 1 through 6 report coefficients on mask manufacturing exposure interacted with month fixed effects from estimates of Equation 3; however, mask manufacturing exposure is constructed using mask manufacturing intensity instead of leave-out mask manufacturing intensity. Robust standard errors are clustered at the sub-District level and p-values are reported in brackets. All columns include destination sub-District fixed effects and month fixed effects. Columns 1 and 2 include firm-product fixed effects, while Columns 5 and 6 estimate coefficients using Poisson pseudo maximum likelihood. Columns 2, 4, and 6 include month fixed effects interacted with controls for Province fixed effects, log population density, log purchases in EBM, the employment rate and secondary school completion and normalize mask manufacturing intensity by province average mask manufacturing intensity before constructing mask manufacturing exposure.

Figure A2: Mask manufacturing exposure increases purchases of masks from manufacturers, decreases mask prices, and reduces COVID-19 infections when parallel pre-trends are imposed

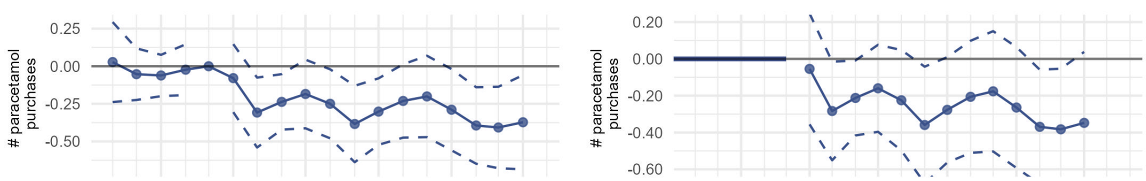
(a) Quantity of masks purchased from manufacturers per adult



(b) Price impacts



(c) log purchases of paracetamol



Notes: Figure A2 plots coefficients on log Mask manufacturing exposure interacted with month fixed effects from estimates of Equation 3. Confidence intervals use robust standard errors are clustered at the sub-District level and presented at 5% significance. All figures include destination sub-District fixed effects and month fixed effects. Figure A2b includes firm-product fixed effects, while Figure A2c estimate coefficients using Poisson pseudo maximum likelihood.

Table A6: Mask manufacturing exposure increases purchases of masks from manufacturers, decreases mask prices, and reduces COVID-19 infections across alternative approaches to including controls

	Dependent variable											
	# manuf. masks / # adults				log mask price				# paracet. purch.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Difference-in-Differences												
log Mask manufacturing exposure$_d$	0.006	0.010	0.002	0.004	-0.052	-0.057	-0.080	-0.084	-0.268	-0.250	-0.291	-0.276
$\times$Post$_t$	(0.002)	(0.003)	(0.001)	(0.002)	(0.031)	(0.034)	(0.030)	(0.032)	(0.140)	(0.139)	(0.138)	(0.138)
	[0.001]	[0.006]	[0.108]	[0.077]	[0.096]	[0.093]	[0.008]	[0.010]	[0.056]	[0.072]	[0.035]	[0.046]
Panel B: Quality standards												
log Mask manufacturing exposure$_d$	0.013	0.020	0.005	0.009	-0.075	-0.079	-0.099	-0.102	-0.202	-0.199	-0.174	-0.170
$\times$Post$_t$	(0.004)	(0.007)	(0.003)	(0.005)	(0.029)	(0.031)	(0.030)	(0.032)	(0.115)	(0.108)	(0.117)	(0.110)
$\times$Pre-universal quality standards$_t$	[0.001]	[0.007]	[0.078]	[0.097]	[0.011]	[0.011]	[0.001]	[0.001]	[0.078]	[0.067]	[0.137]	[0.125]
log Mask manufacturing exposure$_d$	0.004	0.007	0.001	0.002	-0.042	-0.045	-0.072	-0.075	-0.280	-0.260	-0.315	-0.297
$\times$Post$_t$	(0.002)	(0.003)	(0.001)	(0.002)	(0.033)	(0.037)	(0.032)	(0.035)	(0.151)	(0.151)	(0.151)	(0.151)
$\times$Post-universal quality standards$_t$	[0.007]	[0.021]	[0.392]	[0.216]	[0.213]	[0.221]	[0.024]	[0.031]	[0.063]	[0.084]	[0.037]	[0.049]
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson
Firm-product FE					X	X	X	X				
Destination sub-District FE	X	X	X	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X	X	X	X
Normalized intensity		X		X		X		X		X		X
Controls $\times$ Month FE			X	X			X	X			X	X
# observations	4,302	4,302	4,302	4,302	9,748	9,748	9,748	9,748	2,502	2,502	2,502	2,502
# clusters (sub-Districts)	239	239	239	239	239	239	239	239	139	139	139	139

Notes: Columns 1 through 12 report coefficients on mask manufacturing exposure interacted with month fixed effects from estimates of Equation 3. Robust standard errors are clustered at the sub-District level and p-values are reported in brackets. All columns include destination sub-District fixed effects and month fixed effects. Columns 1 through 4 include firm-product fixed effects, while Columns 9 through 12 estimate coefficients using Poisson pseudo maximum likelihood. Columns 3, 4, 7, 8, 11, and 12 include month fixed effects interacted with controls for Province fixed effects, log population density, log purchases in EBM, the employment rate and secondary school completion, and Columns 2, 4, 6, 8, 10, and 12 normalize mask manufacturing intensity by province average mask manufacturing intensity before constructing mask manufacturing exposure.

Appendix references

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