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ABSTRACT

This paper investigates the effect of export shocks on innovation. On the one hand a positive shock increases market size and therefore innovation incentives for all firms. On the other hand it increases competition as more firms enter the export market. This in turn reduces profits and therefore innovation incentives particularly for firms with low productivity. Overall the positive impact of the export shock on innovation is magnified for high productivity firms, whereas it may negatively affect innovation in low productivity firms. We test this prediction with patent, customs and production data covering all French manufacturing firms. To address potential endogeneity issues, we construct firm-level export proxies which respond to aggregate conditions in a firm's export destinations but are exogenous to firm-level decisions. We show that patenting robustly increases more with export demand for initially more productive firms. This effect is reversed for the least productive firms as the negative competition effect dominates.

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1 Introduction

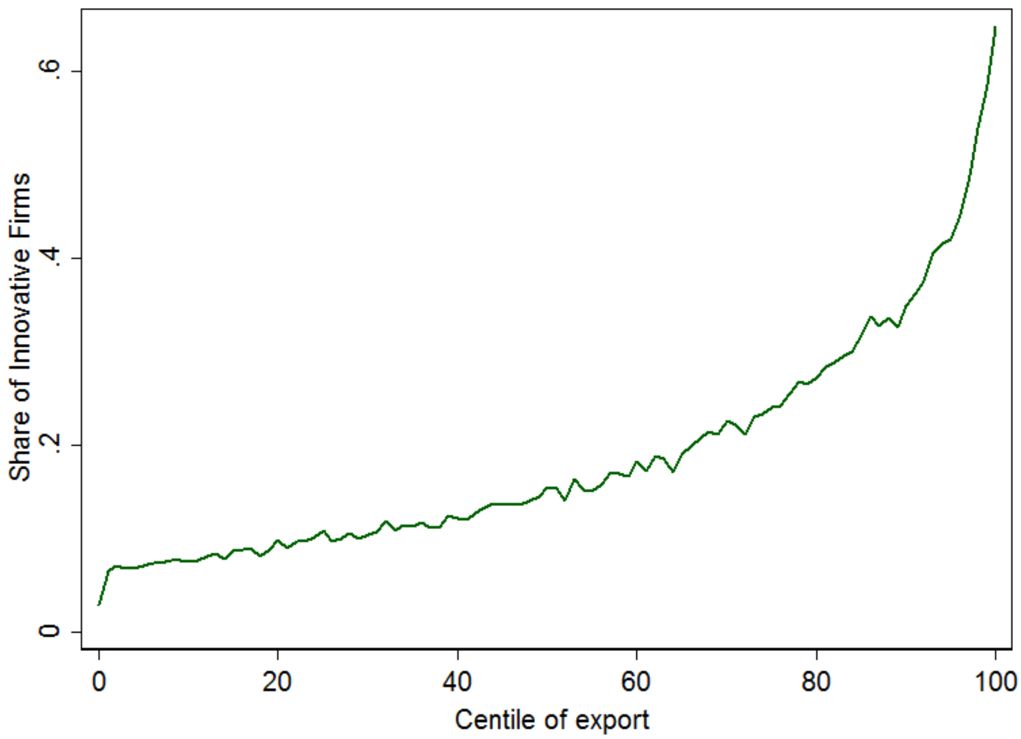
In this paper we combine modeling insights from the literature on firm heterogeneity and trade (see Melitz and Redding, 2014 for a survey) into the new growth theory (e.g., see Aghion and Howitt, 2009). The former literature has focused on the causality link from productivity to trade whereas the latter literature has focused on the reverse link from trade to productivity by investigating the various channels whereby trade liberalization affects innovation-led productivity growth across firms. Our model derives testable predictions on how firms' access to export markets affects innovation; and how this link will vary across exporters. We then take advantage of the availability of exhaustive firm-level data on productivity, trade, and patenting in France to test these predictions.

Figure 1 below motivates our analysis. The curve depicts, for each percentile in exports, the share of French innovative firms within that percentile. It clearly shows a positive relationship between exports and innovation.[1] One of the most striking features that emerges from our merged production-export-innovation dataset is a massive correlation between export and innovation performance across firms. This holds both at the extensive margin (exporters are substantially more likely to innovate, and innovators are more likely to export) as well as the intensive margin (large exporters tend to be big innovators and vice-versa). We describe these relationships in much more detail in Section 3. Does this correlation reflect a causal effect of export on innovation, or the effect of innovation on exports, or both? How does the innovation behavior of a firm react to its export markets' conditions? Our paper is a first attempt at understanding these firm-level patterns connecting innovation and trade using the matching between patenting, balance sheet, and customs exhaustive datasets.

In the first part of the paper we develop a simple model of trade and innovation with heterogeneous firms. The model is one with monopolistic competition and heterogeneous firm capabilities, but adds the innovation dimension of new growth theory to it. It features a continuous set of firms indexed by their heterogeneous production costs. Innovation allows firms to reduce their production costs by an amount that increases with the size of the innovation investment. Think of French firms that export to China. An increase in Chinese demand for products produced by these firms will have two main effects on their innovation incentives. First, a direct market size effect: namely, the expanded market for exports will increase the size of innovation rents and thereby

[1] Obviously the relationship shown in Figure 1 is partly driven by a scale effect: large exporters are larger firms and larger firms are more likely to innovate. However, as we will see below, the distribution of export is more skewed than the distribution of sales or value added. In addition, the positive relationship still exists when centiles of exports intensity (exports divided by sales) are used.

Figure 1: The share of innovators jumps at the top of the export distribution



Notes: Centiles of exports are computed each year from 1995 to 2012 separately and then pooled together. For each centile, we compute the share of innovators. Each centile contains the same number of firms, except for centile 0 that contains all the firms with no export. Manufacturing firms only.

increase those firms' incentives to invest more in innovation. Second, a competition effect: namely, the expanded market for exports will attract new firms into the Chinese market as more firms find it profitable to sell there their product; this in turn will raise competition for exporters into that market. Due to the nature of competition between firms – featuring endogenous markups – this effect dissipates the larger is the firm's market share (and hence its productivity). This competition effect is therefore most salient for French firms with initially lower market shares and higher production costs (these firms will suffer more than -or at the expense of- more efficient exporting firms). Hence our prediction that a positive export shock should raise innovation more in more frontier firms; and that it may induce less innovation for those firms that are far from the frontier.

In the second part of the paper we take this prediction to the data. More specifically, we merge three exhaustive firm-level datasets – patenting, production, and customs data –, which cover the whole population of French firms to analyze how the access to export markets affects the quantity and quality of patents generated by these firms. The patent data are drawn from `PATSTAT` (Spring

2016 version) and contain detailed information on all patents and patent applications from the main patent offices in the world. We use an algorithm developed in Lequien et al. (in progress) that matches a French firm's name with its unique administrative identifier. This allows us to link the innovation activities of a firm with all other firm data sources. The production datasets `FICUS` and `FARE`, from INSEE/DGFiP, contain balance sheet information for each firm registered in France from 1993 to 2012 (total and export sales, number of employees, sector, etc.). French customs trade data (1993-2014) cover nearly comprehensive export flows by firm and destination at a very detailed level of product disaggregation (over 10,000 product categories). We complement these firm-level data sets with bilateral trade data from BACI (Gaulier and Zignago, 2010, updated to cover the period 1995-2013) at the product level (at a slightly higher level of aggregation than our French firm-level export data); and with country-level data (primarily GDP).

To disentangle the direction of causality between innovation and export performance, we construct a firm-level export demand variable following Mayer et al. (2016). This variable responds to aggregate conditions in a firm's export destinations but is exogenous to firm-level decisions (including the concurrent decisions for export-market participation and the forward looking innovation response). We show that: (i) firms that are initially more productive (closer to their sector's technology "frontier") strongly respond to a positive export demand shock by patenting more; (ii) this effect dissipates for firms further from the "frontier" and is reversed for a subset of initially less productive firms. These results confirm the predictions of the model for both a *market size* and a *competition effect* of the export shock. Our theoretical model highlights how an industry equilibrium with endogenous markups is key for this type of competition, which induces a reversal in the innovation response across firms.

Our analysis relates to several strands of literature. There is first the theoretical literature on trade, innovation and growth (see Grossman and Helpman, 1991a,b, Aghion and Howitt, 2009, chapter 13, and more recently Akcigit et al., 2018)[2]. We contribute to this literature by uncovering a new -indirect- effect of market size on innovation working through competition differences within sectors;[3] and by testing the overall effect of export expansion on innovation using exhaustive firm-level data. Second, our paper relates to recent papers on import competition, innovation and productivity growth (see Bloom et al., 2016; Iacovone et al., 2011; Autor et al., 2016; Bombardini

[2] Akcigit et al. (2018) develop and calibrate a new dynamic trade model where firms from different countries compete strategically for leadership in domestic import and export markets. Their model predicts that trade openness encourages innovation in advanced sectors and discourages it in backward sectors.

[3] Dhingra (2013) and Impullitti and Licandro (2018) also develop theoretical models with endogenous firm innovation and endogenous competition (via endogenous markups). Dhingra (2013) focuses on the firm-level trade-offs between innovation and product variety, whereas Impullitti and Licandro (2018) focuses on the consequences of innovation for growth and welfare.

et al., 2017). These papers show that increased import competition induces firms to innovate more in order to escape competition as in Aghion et al. (2005).[4] Instead we look at how the export side of trade affects innovation and analyze a competition effect that varies across producers within a sector. We find very strong empirical confirmation for this type of differential response across firms.

Our paper is most closely related to Lileeva and Trefler (2010) and Bustos (2011), and the ensuing empirical literature connecting exports to innovation at the firm-level.[5] We add to those analyses in three main respects: first, by uncovering an indirect- competition-enhancing effect of increased export market size on innovation; second, by showing that this effect leads to heterogeneous innovation responses to the same market-size shock across firms (strongest for the frontier firms and turning negative for the firms furthest from the frontier); and third, by documenting this type of heterogeneous innovation response – including an innovation reversal for the least efficient firms in a sector.

The remaining part of the paper is organized as follows. Section 2 develops our model of export and innovation, and generates the prediction that the market size effect of a positive export shock, is stronger for more frontier firms. Section 3 briefly presents the data and shows some descriptive statistics on export and innovation. Section 4 describes our estimation methodology and presents our empirical results and Section 5 concludes.

2 Theory

We start with a highly parametrized version of our model in order to highlight the key interactions between market size and competition – leading to innovation reversals for the least productive firms. We then discuss how this result extends to much more general functional forms.

This model is essentially an open economy long-run version of the model in Mayer et al. (2014), augmented with innovation. French firms exporting to some export market destination D are competing with local firms producing in D. We let L denote the number of consumers in that destination, and indexes market size. These consumers have preferences over all varieties available in D. There is a continuum of differentiated varieties indexed by $i \in [0, M]$, where M is the measure of available products. Suppose that the demand for variety q_i is generated by a

[4]Interestingly, in this paper we use *firm-level* competition data, whereas Aghion et al. (2005) as well as previous papers by Nickell (1996) and Blundell et al. (1999) regress innovation and/or productivity growth on *sectoral* measures of product market competition.

[5]In related work, Coelli et al. (2016) document the patenting response of firms in response to the Uruguay round of tariff levels.

representative consumer in country D with additively separable preferences with sub-utility:[6]

$$u(q_i) = \alpha q_i - \frac{\beta q_i^2}{2},$$

where $\alpha > 0$ and $\beta > 0$.

As this consumer makes no difference between a French or a locally produced variety, the output, profit and revenues for the French exporters and local producers have the same expression. For simplicity, we assume that both types of firms have access to the same innovation technology, which leads to similar innovation decisions, but the results can be easily extended without this assumption.

2.1 Consumer optimization

This representative consumer facing prices p_i solves:

$$\max_{q_i \geq 0} \int_0^M u(q_i) di \quad \text{s.t.} \quad \int_0^M p_i q_i di = 1.$$

This yields the inverse residual demand function (per consumer):

$$p(q_i) = \frac{u'(q_i)}{\lambda} = \frac{\alpha - \beta q_i}{\lambda}, \tag{1}$$

where $\lambda = \int_0^M u'(q_i) q_i di > 0$ is the corresponding Lagrange multiplier, also equal to the marginal utility of income. Given the assumption of separable preferences, this marginal utility of income λ is the unique endogenous aggregate demand shifter. Higher λ shifts all residual demand curves downwards; we thus interpret this as an increase in competition for a given exogenous level of market size L.

2.2 Firm optimization

Consider a (French or domestic) firm with marginal cost c facing competition λ. This firm chooses the output per consumer $q(c; \lambda)$ to maximize operating profits $L[p(q)q - cq]$. The corre-

[6] As we argue below, our analysis can be extended to a broader class of preferences that satisfy Marshall's Second Law of Demand (such that residual demand becomes more inelastic as consumption increases).

sponding first order condition yields

$$q(c;\lambda) = \frac{\alpha - c\lambda}{2\beta}, \tag{2}$$

so long as the firm's cost is below α/λ; the remaining firms with higher cost do not produce. This output choice in turn leads to the maximized profit per consumer

$$\pi(c;\lambda) = \frac{(\alpha - c\lambda)^2}{4\beta\lambda}.$$

In particular, we see that both output and profit are decreasing in both firm level cost c and the endogenous competition measure λ. More productive firms (with lower cost c) are larger and earn higher profits than their less productive counterparts; and an increase in competition λ lowers production levels and profits for all firms.

2.3 Innovation choice

A firm is characterized by its baseline cost $\tilde{c}$. It can reduce its marginal cost of production c below its baseline cost by investing in innovation. More formally, we assume that

$$c = \tilde{c} - \varepsilon k,$$

where k is the firm's investment in innovation and $\varepsilon > 0$; and we assume that the cost of innovation is quadratic in k, equal to $c_I k + \frac{1}{2} c_{I2} k^2$.[7] Thus a firm with baseline cost $\tilde{c}$ will choose its optimal R&D investment $k(\tilde{c};\lambda)$ so as to maximize total profit:

$$\Pi(\tilde{c}, k; \lambda) = L\pi(\tilde{c} - \varepsilon k; \lambda) - c_I k - \frac{1}{2} c_{I2} k^2.$$

The optimal R&D investment $k(\tilde{c};\lambda)$, if positive, satisfies the first order condition:

$$\varepsilon Q(\tilde{c}, k; \lambda) = c_{I2} k + c_I, \tag{FOC}$$

[7] Since we only consider a single sale destination D for our firms, we are implicitly assuming that the innovation is directed at the delivered cost to consumers in D. We should thus think of innovation as specific to the appeal/cost trade-off to consumers in D. As we discuss in further detail later, our analysis extends to the more general case where innovation affects (and responds to) changes in other destinations, as long as competition in other destinations does not respond to changes in market D (namely market size).

where $Q(\tilde{c}, k; \lambda) \equiv Lq(\tilde{c} - \varepsilon k; \lambda) = L[\alpha - (\tilde{c} - \varepsilon k)\lambda]/2\beta$ is the total firm output (across consumers) produced by a firm with baseline cost $\tilde{c}$ and innovation k. We assume that the baseline cost $\tilde{c}$ is bounded below by $\tilde{c}_{\min}$ such that $\tilde{c}_{\min} - \varepsilon k(\tilde{c}_{\min}; \lambda) = 0$, or equivalently

$$\tilde{c}_{\min} = \frac{\varepsilon}{c_{I2}} \left(\frac{\varepsilon L \alpha}{2\beta} - c_I \right).$$

This in turn ensures that the post-innovation marginal cost is bounded away from zero, even for the most productive firms.

Figure 2 depicts the optimal innovation choice at the intersection between the marginal cost (MC, right-hand side of FOC) and the marginal benefit of innovation (MB, left-hand side of FOC). As long as the marginal benefit is above the marginal cost of investing in R&D, the firm wants to increase innovation, because the marginal profit made by investing one more unit of R&D, exceeds its marginal cost. We assume that the second order condition holds, which ensures that the slope of the marginal cost is strictly larger than the slope of the marginal gain (otherwise firms may end up with infinite innovation), namely:

$$c_{I2} > \varepsilon \frac{\partial Q}{\partial k} = \frac{\varepsilon^2 \lambda L}{2\beta}. \tag{SOC}$$

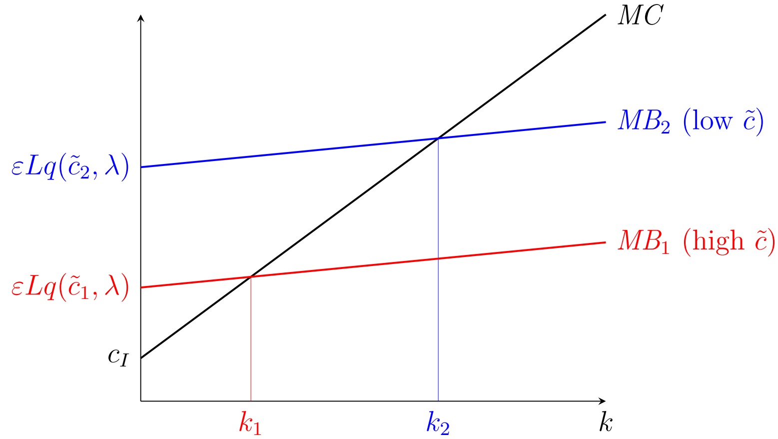
When comparing a more productive firm (with lower baseline cost, depicted by the blue curve) and a less productive firm (with higher baseline cost, depicted by the red curve), we see that both firms face the same marginal cost curve and their marginal gain curves have the same slope. Only the zero intercepts of the two marginal gain curves are different: the lower $\tilde{c}$ firms have a higher intercept, thus a higher marginal gain, and therefore invest more in R&D. Firms with sufficiently high baseline costs do not innovate, as the zero intercept of their marginal gain curves falls below c_I, so that even their first innovation unit would not be worth its cost. These are firms with baseline costs above the baseline cost of the marginal innovator, which is equal to:

$$\widehat{C}_I = \frac{1}{\lambda} \left(\alpha - \frac{2\beta c_I}{\varepsilon L} \right). \tag{3}$$

2.4 The direct impact of an increase in market size or competition on innovation

In the next section, we describe how an increase in market size L induces an endogenous increase in competition λ in the destination market D. To build intuition on the combined impact of these

Figure 2: Optimal innovation is higher for more efficient firms



demand-side changes for innovation, we first consider these effects separately. We first analyze the direct effect of an increase in market size L, holding the competition level λ constant. At each firm's current innovation choice $k(\tilde{c}; \lambda)$, this triggers a proportional increase in firm output, and an upward shift in the marginal benefit of innovation, inducing all firms to increase innovation.

Figure 3 shows this innovation response for firms with different baseline costs. Both the intercept and the slope of the marginal gain curve increase. We see how this leads to our unambiguous prediction of higher innovation for all firms. Given our assumptions on the benefits and costs of innovations, this leads to higher innovation responses for more productive firms:

$$\frac{\partial^2 k}{\partial L \partial \tilde{c}} < 0.$$

This increase in market size also induces some firms to begin R&D (higher $\widehat{C}_I$, see 3).

We now consider the effect of an increase in competition λ, holding market size L constant. At each firm's current innovation choice $k(\tilde{c}; \lambda)$, this triggers a decrease in firm output (see 2). However, unlike the case of a change in market size L, this output response is no longer proportional across firms: high cost firms bear the brunt of the competition increase and disproportionately lose market share. Even though all firms respond by reducing innovation, this reduction in innovation is most pronounced (larger) for those high cost firms:

$$\frac{\partial^2 k}{\partial \lambda \partial \tilde{c}} < 0.$$

This contrasts with the case of a market size decrease (leading to proportional output decreases), which would lead to bigger innovation reductions for low cost firms instead. In the limit for

Figure 3: Direct market size effect (increase in L)

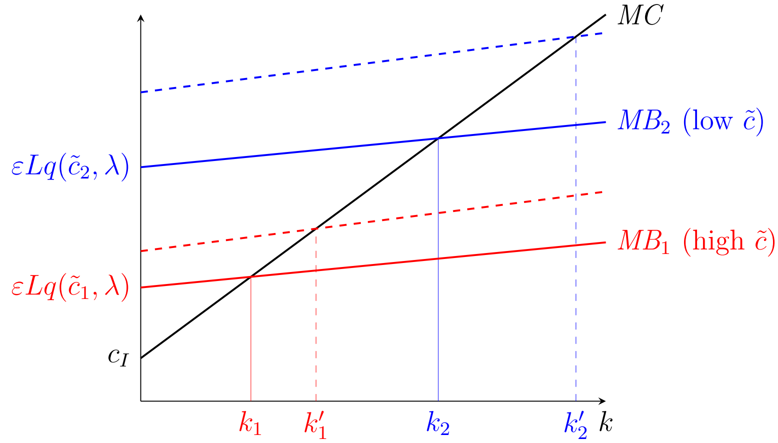
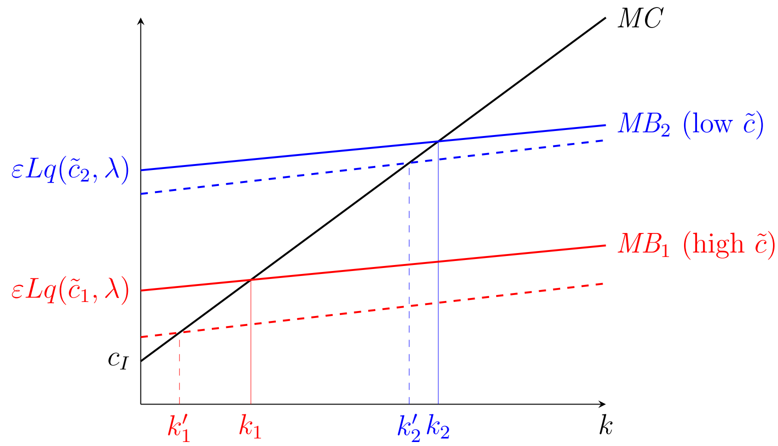


Figure 4: Competition effect (increase in λ)



the most efficient firms (with baseline cost approaching $\tilde{c}_{\min}$), the negative impact of increased competition on innovation dissipates completely (see FOC).

Figure 4 shows this innovation response for firms with different baseline costs. The increase in competition decreases the marginal benefit of innovation, but substantially more for the high cost firm – because the intercept decrease is larger (recall that the slope of the marginal benefit curve does not change with the firm's baseline cost).[8] Thus, the high cost firm's reduction in innovation is most pronounced. The competition increase also induces some firms to stop R&D (lower $\widehat{C}_I$, see 3).

In the next subsection we endogenize the competition variable λ by introducing a free entry

[8]The new dotted marginal benefit curve remains below the old one at least until it meets the marginal cost curve, even though an increase in competition increases the slope of the marginal benefit curve.

condition.

2.5 The induced competition effect of increased market size

We now describe how the equilibrium competition level λ in country D is endogenously determined and show that λ increases with L. This equilibrium involves all the firms operating in D, including both the French exporters to D along with the domestic producers in D. However, in the long-run with entry of domestic producers into D, we show that the equilibrium competition level λ is determined independently of the export supply to D (which then only impacts the number of domestic entrants and producers).[9] Since innovation is inherently forward looking, we focus on these long-run implications for competition.

Let $\Gamma_D(\tilde{c})$ denote the cumulative distribution of baseline costs $\tilde{c}$ among domestic producers in D. We assume that $\Gamma_D(\tilde{c})$ has support on $[\tilde{c}_{0D}, +\infty)$ with $\tilde{c}_{0D} > \tilde{c}_{\min}$. Let F_D denote the fixed production cost faced by those domestic firms in D. Since a firm's operating profit is monotonic in its baseline cost $\tilde{c}$, producing for the domestic market D is profitable only for domestic firms with a baseline cost $\tilde{c}$ below a cutoff value $\widehat{C}_D$ defined by the zero profit condition:

$$\Pi(\widehat{C}_D, 0; \lambda) = F_D, \tag{ZCP}$$

where we have assumed that $\widehat{C}_D > \widehat{C}_I$ so that the firm with the cutoff cost $\widehat{C}_D$ does not innovate (and hence does not incur any innovation cost). In the long-run, entry is unrestricted subject to a sunk entry cost F_D^E. In equilibrium, the expected profit of a prospective entrant will be equalized with this cost, yielding the free-entry condition:

$$\int_{\tilde{c}_{0D}}^{\widehat{C}_D} \left[\Pi(\tilde{c}, k(\tilde{c}; \lambda); \lambda) - F_D\right] d\Gamma_D(\tilde{c}) = F_D^E. \tag{FE}$$

Proposition 1 *The two conditions (ZCP) and (FE) jointly determine a unique pair $(\lambda, \widehat{C}_D)$.*

The proof is developed in A.1. It relies on the fact that (ZCP) is downward-sloping whereas (FE) is upward sloping in $(\widehat{C}_D, \lambda)$ space. For simplicity, we have abstracted from any export profits for the domestic firms. This is inconsequential for the qualitative predictions of our model that we emphasize below – so long as changes in country D (in particular its market size) do not affect

[9] This is not the case in the short-run, where the export supply to D affects both the competition level λ as well as the number of domestic producers.

the equilibrium competition levels in those export markets. Essentially, the key assumption is that market D is small relative to the size of the global export market.[10]

Proposition 2 *An increase in market size L in D leads to an increase in competition λ in the long-run.*

Proof. We prove this proposition by contradiction. If λ were to decrease, then the cutoff $\widehat{C}_D$ would have to increase (see (ZCP)). Since $\pi(c;\lambda)$ is decreasing in λ, then $\Pi(\tilde{c},k;\lambda)$ must also increase for any given innovation level k when λ decreases. Given the optimization principle, $\Pi(\tilde{c},k(\tilde{c};\lambda);\lambda)$ must also increase. This, together with an increase in the cutoff $\widehat{C}_D$, represents a violation of the (FE) condition. Thus competition λ must increase when L increases. ■

2.6 The overall effect of increased market size on innovation

We now analyze the overall effect of an increase in market size L on innovation resulting from both the direct market size effect and the induced competition effect (increase in λ). Based on our previous discussion, we already know that the overall innovation response for the most efficient firms (those firms with the lowest baseline costs) will be positive. The reason is that the negative impact of the induced increase in competition on innovation dissipates for the most efficient firms, so that the positive direct market size effect must prevail for those firms.

As we move away from the technology frontier towards less efficient firms, the negative impact of increased competition on innovation strengthens and is no longer negligible. This leads to lower and lower innovation responses for firms as we move away from the technology frontier up the baseline cost scale. The only remaining question is whether the overall impact of an increase in L on innovation can indeed become negative for operating firms with sufficiently high baseline costs. In order to show that this is the case, we first point out that – in response to any changes in market conditions λ and L – innovation co-moves monotonically with firm output as well as its output at a *given* innovation level k.

[10]More precisely, the free entry condition can be extended to incorporate the (net) export profits Π_{-D} earned in other destinations:

$$\int_{\tilde{c}_{0D}}^{\widehat{C}_D} \left[\Pi(\tilde{c},k(\tilde{c};\lambda);\lambda) - F_D + \Pi_{-D}(\tilde{c},k;\{\lambda_{-D}\})\right] d\Gamma_D(\tilde{c}) = F_D^E,$$

where $\{\lambda_{-D}\}$ denotes the vector of competition levels in countries other than D. So long as these competition levels $\{\lambda_{-D}\}$ do not respond to changes in D, the export profits shift up the marginal benefit of innovation in (FOC) by an amount that does not depend on λ or L. This marginal benefit curve will remain an increasing function of innovation k and will shift up with any market-wide change in D that increases firm output $Q(\tilde{c},k;\lambda)$ at fixed innovation k. This is the key property that we rely on in our comparative statics for the impact of market size and competition.

Proposition 3 *For a given innovating firm, innovation, output and output holding k fixed all move comonotonically in response to a change in the market size L.*

The proof is a straightforward extension of the first and second order conditions for optimal innovation depicted in Figure 2. Any change in market conditions L or λ leading to an increase in firm output $Q(\tilde{c}, k; \lambda)$ at constant innovation k results in an upward shift of the marginal benefit curve. This induces an increase in the optimal level of innovation (given the second order condition ensuring that the marginal benefit curve cuts the marginal cost curve from above). This innovation response further re-enforces the increase in firm output $Q(\tilde{c}, k(\tilde{c}; \lambda); \lambda)$.

We have just shown that any changes in market size or competition that increase a firm's output choice (at its current innovation level) will induce this firm to increase innovation – and vice-versa. In order to show that high cost firms reduce innovation in response to an increase in market size, we need only show that this market size increase induces those firms to reduce output at their current innovation levels (due to the increase in competition λ). This output response is given by:

$$\left.\frac{dQ}{dL}\right|_{k \text{ fixed}} = \frac{\partial Q}{\partial L} + \frac{\partial Q}{\partial \lambda}\frac{d\lambda}{dL} = q(\tilde{c} - \varepsilon k; \lambda) - L\frac{\tilde{c} - \varepsilon k}{2\beta}\frac{d\lambda}{dL}. \tag{4}$$

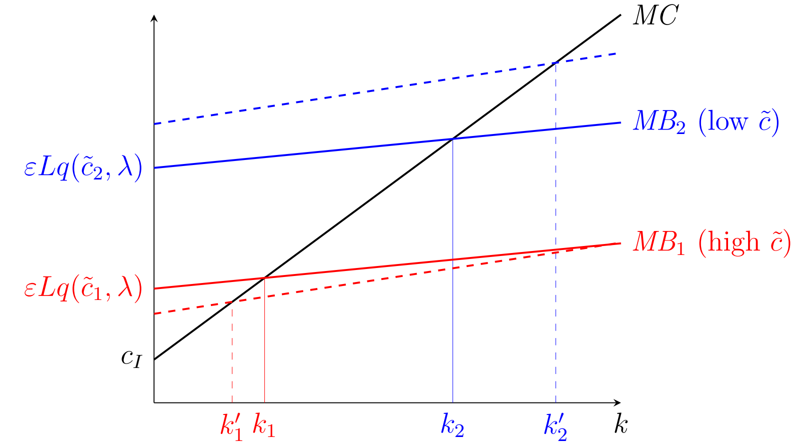
As a firm's baseline cost $\tilde{c}$ increases, the direct positive impact of the market size increase diminishes, whereas the negative impact due to increased competition strengthens. The positive impact shrinks to zero in the limit as a firm's marginal cost approaches the choke price α/λ that induces no consumer demand $q(\alpha/\lambda; \lambda) = 0$. Thus, the total output response must be negative for at least some high cost firms. So long as those firms innovate, their innovation response to a market size increase will be negative. Hence, whenever the set of innovating firms is broad enough – the innovation threshold $\widehat{C}_I$ is high enough – then there will be an innovation reversal within this set of firms. This will be ensured so long as the innovation cost c_I is low enough, along with a low fixed cost F to ensure that production is profitable for all innovating firms. More generally, in the Appendix we establish:

Proposition 4 *a) For any cost distributions Γ and Γ_D, there exists values of c_I and F such that some high cost firms reduce their innovation when the market size L increases.*

b) For any values of c_I and F, there exists cost distributions Γ and Γ_D and a range of L such that some high cost firms reduce their innovation when the market size L increases within that range.

Figure 5 illustrates this parameter configuration leading to an innovation reversal for the high cost firm in response to an increase in market size L. Lastly, we note that this innovation reversal

Figure 5: Overall response of innovation to an increase in market size L



applies to French exporters in the same way that it does for domestic producers in D. It also applies to a much more general version of our model without specific functional form representations for the cost-saving benefit of innovation (replacing ε with a function of the baseline cost $\tilde{c}$ and innovation k); the cost of innovation (a convex function of innovation k); and for preferences. The key feature of the optimal innovation choice – linking the direction of the innovation response with the direction of the change in firm output at a *constant* innovation level – would continue to hold. Thus, an innovation reversal will occur for high baseline cost firms so long as a market size increase induces a reduction in output for those firms. As discussed in Mayer et al. (2014), this output reversal in response to market size increases will occur whenever residual demand satisfies Marshall's Second Law of Demand – whereby demand becomes more inelastic with consumption. Importantly, such a reversal cannot occur under C.E.S. preferences and exogenous markups. The competition increase induced by the endogenous response of the markups is a critical necessary ingredient for the prediction of both output – and therefore innovation – reversals.

3 Exporters and Innovators: data and descriptive statistics

In this section, we briefly present our datasets and show some descriptive evidence on the link between firms' innovation and exports. Further details about data construction can be found in Appendix B.

3.1 Data sources

We build a database covering all French firms and linking export, production and innovation data from 1994 to 2012. Our database draws from three sources: (i) French customs, which reports yearly export flows at a very disaggregated HS8 product level (representing over 10,000 manufacturing products) by destination; (ii) Insee-DGFiP administrative fiscal datasets (`FICUS` and `FARE`), which provide extensive production and financial information for all firms operating in France; (iii) the Spring 2016 vintage of `PATSTAT` patent dataset from the European Patent Office, which contains detailed information on all patent applications from many patent offices in the world. In our analysis we will focus on all patent applications and on patents filed in some specific patent offices (see section 4.2 and Appendix B for details).

Although each French firm has a unique identifying number (Siren) across all French databases, patent offices do not identify firms applying for patents using this number but instead using the firm's name. This name may sometime carry inconsistencies from one patent to another and/or can contain typos. Various algorithms have been developed to harmonize assignees' names (for example this is the case of the OECD Harmonized Assignee Name database, see Morrison et al., 2017 for a review) but none of those have been applied specifically to French firms. One notable exception is the rigorous matching algorithm developed in Lequien et al. (in progress) to link each patent application with the corresponding French firms' Siren numbers, for all firms with more than 10 employees. This new method, based on supervised learning and described in Appendix B.4, provides significant performance improvements relative to previous methods used in the empirical patent literature: Its recall rate (share of all the true matchings that are accurate) is 86.1% and its precision rate (share of the identified matches that are accurate) is 97.0%. This is the matching procedure we use for our empirical analysis in this paper.

Finally, we use CEPII's `BACI` database of bilateral trade flows at the HS6 product level (covering more than 5,000 manufacturing products, see Gaulier and Zignago, 2010) to construct measures of demand shocks across export destinations over 1995-2012.

Sample restrictions

Although our main firm-level administrative data source is comprehensive, with more than 47.1 million observations spanning over 7.3 million different firms from 1995 to 2012, we restrict our data sample for several reasons. The first is due to the matching with patent data mentioned above, which is most complete for firms above 10 employees. We therefore impose this size restriction, which drops a large number of firms but a relatively small share of aggregate French production:

17.1% of employment, 15.6% of sales, and 13.6% of exports (predominantly within EU exports). Second, we restrict our attention to private business corporations (legal category 5 in the Insee classification). We thus drop state-owned firms, self-employed businesses, and non-profit organizations as we focus on profit-maximizing firms. This further reduces our sample from 1.7 million to 835,000 firms. Yet, the bulk of aggregate employment (74.2%), sales (77.7%), and exports (77.2%) remain in our dataset after imposing these restrictions. These remaining firms are matched with an average of 27,640 patents per year in `PATSTAT`. Lastly, since our detailed customs trade data only covers goods trade (and not services), we will further restrict our sample to the manufacturing sector for most of our analysis.[11] This reduces our working sample to 105,000 firms. Nevertheless the bulk of French aggregate exports and innovation are still concentrated in manufacturing as only 20.6% of aggregate exports and 33% of patents are recorded outside of this sector.

Our dataset does not allow us to properly take into account the case of multinational groups, an issue which often arises when dealing with national firm level data. Multinational groups tend to break the relationship between export shocks and patenting since these groups may locate their R&D activities in different countries from the location of production. In particular, the R&D activity for production based in France may be located elsewhere under a different entity of a multinational's group. In this case, we will not record the appropriate link between the export shocks for this producer and an induced innovation (patents). This measurement issue works against our obtained results of a positive response of patenting to export shocks that is increasing with a firm's proximity to its industry frontier. Thus, we conjecture that our results would be strengthened if we had the needed information to exclude broken production/R&D links amongst the multinational groups in our sample.

3.2 Sector breakdown and skewness

Table 1 shows the breakdown of those firms across sectors, along with their average employment, exports, and patents (per firm) for 2007.[12] As has been widely reported in the empirical literature on micro-level trade patterns, many firms are only occasional exporters: they export in some years, but not in others. This pattern is even more pronounced for innovation: even firms with substantial ongoing R&D operations do not typically file patent applications year in and year out. We therefore use the broadest possible cross-year definition to classify firms as exporters and innovators. We label a firm as an *exporter* if it has exported at least once between 1993-2012;

[11] Although the customs data also covers the wholesale sector, we also exclude those firms as they do not produce the goods that they export.

[12] Throughout, we define sectors at the 2-digit level of the European NACE rev2 classification. We also eliminate the tobacco sector (# 12) as it only contains two firms.

and as an *innovator* if it has filed at least one patent application between 1995-2012.[13] Thus, our reported export participation rates in Table 1 are higher than in other studies. However, even with this broadest classification, innovators represent only a small minority of manufacturing firms. For comparison, Table 1 also reports the share of exporters and innovators based on the more standard definition of current year (2007 for this table) exporting or patenting activity – shown in parentheses.

Table 1: Exports and innovation in the manufacturing sector

Sector	Description	Firms	Emp	Export	% Exporter	Patents	% Innov.
10	Food products	8,814	43	1,847	41 (26)	20	3 (0)
11	Beverages	1,463	47	5,974	80 (59)	11	2 (0)
13	Textiles	1,802	37	2,335	86 (63)	91	12 (2)
14	Wearing apparel	1,558	39	2,577	80 (59)	49	5 (1)
15	Leather	492	56	2,566	85 (59)	38	9 (2)
16	Wood	2,432	29	790	64 (36)	16	5 (1)
17	Paper	2,950	44	2,056	79 (44)	86	7 (1)
18	Printing	842	24	167	53 (20)	5	3 (0)
19	Coke	171	225	75,957	92 (69)	3,061	24 (9)
20	Chemicals	1,229	116	17,607	94 (79)	1,992	21 (6)
21	Basic pharmaceutical	357	288	42,065	96 (82)	2,808	35 (13)
22	Rubber and plastic	2,745	80	3,820	86 (64)	339	21 (6)
23	Other non-metallic	2,158	63	2,320	65 (38)	272	11 (2)
24	Basic metals	1,648	80	12,487	66 (44)	147	12 (3)
25	Fabricated metal	8,392	36	1,125	67 (40)	82	9 (2)
26	Computer and electronic	3,511	85	7,620	73 (54)	769	23 (8)
27	Electrical equipment	447	106	8,812	91 (70)	1,764	26 (8)
28	Machinery and equipment	4,668	80	8,252	79 (58)	558	24 (7)
29	Motor vehicles	791	61	2,549	79 (47)	173	15 (3)
30	Other transport equipment	558	215	54,911	83 (56)	2,293	18 (7)
31	Furniture	1,146	34	598	67 (36)	14	7 (1)
32	Other manufacturing	1,017	41	2,472	82 (58)	321	12 (3)
33	Repair of machinery	3,430	28	302	54 (23)	25	6 (1)
	Aggregate manufacturing	52,621	57	4,654	68 (44)	288	11 (3)

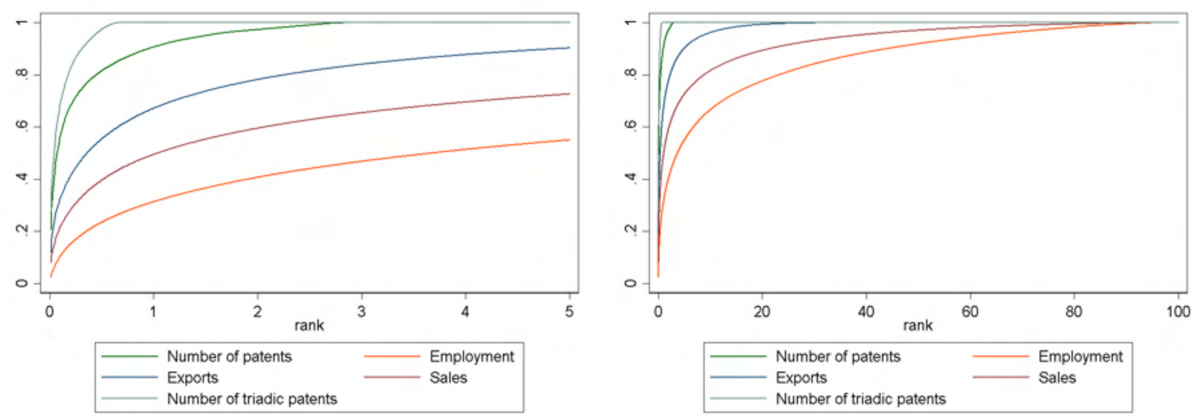
Notes: This table presents the number of firms, average employment, average export (in thousands of Euros), average number of patents (in thousands), and the shares of exporters and innovators (cross-year definitions). The shares in parentheses are calculated based on current year export participation or patent filing. Data are for 2007.

Even within the minority set of innovators, patenting activity is extremely skewed. This is

[13]The initial year for both ranges do not coincide in order to reflect our subsequent empirical analyses. We will use prior years of export data to construct exogenous export share weights (see section 4.1 for more details).

Figure 6: Lorenz curves - patents are more concentrated than exports, sales and employment

(a) Top 5 percentiles (b) Whole distribution



Notes: Lorenz curves plot cumulative distribution function for patents, triadic patents, employment, export and sales. Data are for manufacturing firms.

clearly visible in Figure 6, which plots the Lorenz curve for patents and triadic patent families at manufacturing firms in 2007, along with the Lorenz curves for exports, sales, and employment. Figure 6 confirms the previously reported finding that firm-level exports are significantly more skewed than sales and employment (e.g. see Mayer and Ottaviano, 2008 and Bernard et al., 2016): 1% of firms account for 67% of aggregate exports in 2007, whereas the top 1% of firms based on total size account for 50% of sales (ranked by sales) and 31% of employment (ranked by employment). But Figure 6 also shows that patenting is even significantly more skewed than exporting: 1% of all firms account for 91% of patents in 2007. And less than 1% of firms own all the triadic families - i.e. patent families which include patents filed in Asia, Europe and in the USA, see Section 4.2). Indeed fewer than 2.9% of manufacturing firms have patented in 2007. This fraction is significantly smaller than our previously reported 11% share of innovators in Table 1 measured across our full sample years. Similarly, only 44% of manufacturing firms report any exporting activity for 2007 compared to a 68% share when exporting is measured across our full sample years.

These univariate statistics for patenting and exporting do not capture the massive overlap between these two activities across firms – which we investigate in more detail below.

3.3 The innovation-export nexus

Looking across our sample years (1995-2012), Table 2 reports different size-related performance measures (averages per firm) based on their exporter and innovator classification. This table confirms the well-documented size differential in favor of exporters. However, several new salient features regarding innovators pop-out from this table: 1) Innovating firms are massively concentrated among exporters: only 5% of innovators do not report any exporting; 2) non-exporting innovators do not look very different than non-exporting non-innovators, and the various measures of firm size (employment, sales, value-added) respectively for innovators and non-innovators among non-exporters remain close to each other;[14] 3) these same measures of firm size differ markedly between innovators and non-innovators among exporters: innovators employ on average 4.5 times more workers and produce 7-8 times more output and value-added than non-innovating exporters. They export almost 10 times more than non-innovators and reach more than three times the number of export destinations. These size differentials are several times larger than those between exporters and non-exporters. In the aggregate, this small subset of innovators accounts for over half of French manufacturing exports.

Table 2: Exporters and innovators are bigger

	Non-exporter		Exporter		Total
	Non-innovator	Innovator	Non-innovator	Innovator	
Firms	45,789	392	52,043	6,893	105,117
Employment	17	20	51	233	59
Sales	2,147	2,460	11,499	69,200	13,982
Value Added	639	883	2,733	16,091	3,332
Age	14	15	20	22	18
Export	0	0	2,463	22,875	3,622
Countries	0	0	5	18	5
Patents	0	0.2	0	2.6	0.2

Notes: This table presents basic descriptive statistics across four categories of manufacturing firms whether they innovate, export, both or none. Employment is given in full-time equivalent on average over the year and exports, sales and value added are in thousand of euros. Countries is the number of destination countries for exports. Employment, Sales, Value Added, Age, Exports, Countries and Patents are taken as a yearly average over the whole period 1995-2012.

In order to compare exporters to non-exporters and innovators to non-innovators, within specific

[14]This is not the case outside of the manufacturing sector. In those other sectors, non-exporting innovators are substantially bigger than their non-exporting and non-innovating counterparts. We conjecture that this is driven by the fact that exporting no longer serves the same performance screening function outside of manufacturing.

groups, we compute export and innovation premia. Consider first the exporter premia reported in the top panel of Table 3. These premia are generated by regressing the performance measure of interest (listed in the rows) on our exporter indicator – with each cell representing a separate regression. Column 1 includes no other controls; Column 2 adds a 2-digit sector fixed effect (see Table 1); and Column 3 controls for firm employment, in addition to the sector fixed effect. Since we are using a broad cross-year definition for exporter status, we expect these premia to be lower than measures based on current-year exporter status since firms who drop in and out of export markets tend to be substantially smaller than year in year out exporters. This is the case for the premia in column 1 compared to similar numbers reported by Bernard et al. (2016) for U.S. firms in 2007. Yet, once we control for sectors in column 2, the reported premia become much more similar. In particular, we find that even within sectors, exporters are substantially larger than non-exporters. And we also find that large differences in productivity and wages in favor of exporters persist after controlling for firm employment (within sectors).

Table 3: Export and innovation premia

Panel 1: Premium for being an exporter (among all manufacturing firms)

	(1)	(2)	(3)	Obs.	Firms
log Employment	0.854	0.767		937,050	91,563
log Sales	1.616	1.478	0.417	979,413	104,368
log Wage	0.132	0.097	0.109	935,489	91,525
log Value Added Per Worker	0.217	0.171	0.175	923,535	90,876

Panel 2: Premium for being an innovator (among all exporting manufacturing firms)

	(1)	(2)	(3)	Obs.	Firms
log Employment	1.043	0.997		645,522	58,121
log Sales	1.284	1.239	0.197	656,218	58,803
log Wage	0.125	0.095	0.109	644,533	58,104
log Value Added Per Worker	0.203	0.173	0.179	635,144	57,720
log Export Sales (Current period exporters)	2.018	1.911	0.806	433,456	56,509
Number of destination countries	13	11	7	663,004	58,936

Notes: This table presents results from an OLS regression of firm characteristics (rows) on a dummy variable for exporting (upper table) or patenting (lower table) from 1994 to 2012. Column 1 uses no additional covariate, column 2 adds a 3-digit sector fixed effect, column 3 adds a control for the log of employment to column 2. All firm characteristic variables are taken in logs. All results are significant at the 1 percent level. Upper table uses all manufacturing firms whereas lower table focuses on exporting manufacturing firms.

In the bottom panel, we focus on the subset of exporters from the top panel, and report the *additional* premia in favor of innovators within this subset. As with the top panel, those premia are calculated by running separate regressions on our innovator indicator. Even within this subset of bigger and better performing firms, innovators stand out: they are substantially bigger, more productive, and have larger total wage bill. They also export substantially more (and to more destinations) than non-innovative exporters. All these differences persist within sectors and controlling for firm employment.

Even these large premia do not fully reflect the concentration of innovative and exporting activities within the more restricted subset of firms that are both exporters and innovators. Figure 1 plots the share of innovating firms for each percentile of the firm export distribution. We see that the innovative firms are highly concentrated within the top percentiles of the export distribution. At the 80th percentile of the export distribution, 30% of the firms have some patenting experience. And the increase in the share of innovative firms with the percentile of the export distribution is highly convex. Above the 95th percentile of the export distribution, a majority of firms are innovators; in the top percentile, 68% of the firms are innovators. Those firms in the top export percentile account for 41% of the aggregate share of French patents.

4 Empirical framework and results

4.1 Identification strategy: firm-level export demand shocks

We have just documented the strong correlation between exports and innovation in the cross-section of French manufacturing firms. However, this correlation does not shed light on the direction of causation: from innovation to exports (a major innovation leads to growth in export demand and entry into new export markets), or from exports to innovation (as we emphasize in our theoretical comparative statics). Moreover, other firm-level changes could generate concurrent changes in both innovation and exports (for example, a new management team). Thus, to identify the causal relationship from exports to innovation, we need to identify a source of variation in firm exports that is exogenous to changes within the firm (and in particular to the innovation activity of the firm). We follow Mayer et al. (2016) in building such a measure of exogenous export demand.

To construct these export demand shocks, consider a French exporter f who exports a product s to destination j at an initial date t_0. Let M_{jst} denote the aggregate import flow in product s into country j from all countries except France at time $t > t_0$. M_{jst} reflects the size of the (s, j) export market at time t. We then sum M_{jst} across destinations j and products s weighted by the relative importance of market (s, j) in firm f's exports at the initial date t_0. The underlying idea is that subsequent changes in destination j's imports of product s from the world (excluding France) will be a good proxy for the change in export demand faced by this firm. By excluding French exports to this destination, we seek to exclude sources of variation that originate in France and may be correlated with changes for the firm.[15] We then scale the weighted export demand variable by the firm's initial export intensity (at t_0) so that our demand shock scales proportionately with a firm's total production. (As a firm's export intensity goes to zero, so does the impact on any export shock on total production.)

More precisely, let X_{fjst_0} denote firm f's export flow to market (j, s) at time t_0. This is the firm's first observed export year in our sample.[16] The export demand shock for firm f at time t is

[15] Another distinct potential source of endogeneity may arise in markets where a French firm has a dominant position. In this case, imports into those markets may respond to this firm's decisions (including innovation). We address this issue in Section 4.5.3.

[16] We consider this firm to be an exporter only if we observe positive exports in both customs data (so we can

then:

$$D_{ft}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst}, \tag{5}$$

where the weight $(X_{ft_0}^*/S_{ft_0}^*)(X_{fjst_0}/X_{ft_0})$ represents firm f's initial share of sales of product s to destination j and $X_{ft_0} = \sum_{j,s} X_{fjst_0}$ represents the firm's total exports. The asterisks on firm f's initial export intensity $X_{ft_0}^*/S_{ft_0}^*$ indicate that the underlying data for total exports $X_{ft_0}^*$ and sales $S_{ft_0}^*$come from the production data (as opposed to customs data which we use to calculate the destination/product specific market shares).[17]

We note that the time variation in our demand shock $D_{ft}^{M_s}$ only stems from the world export flow M_{jst} and not the firm-level weights, which are fixed in the initial export period t_0. We expect that a firm's innovation response at time $t > t_0$ will induce changes to its pattern of exports at time t and beyond, including both intensive margin responses (changes in exports for a previously exported product s to a destination j) and extensive margin responses (changes in the set of products s sold across destinations j). By fixing the firm-level weights in the initial period t_0 (including the extensive margin set of products and destinations), we exclude this subsequent endogenous variation from our demand shock.

We will also experiment with an alternate measure of this demand shock using more aggregated data (across products). We thus aggregate both the world and the firm's export shares at the 3-digit ISIC level:

$$D_{ft}^{M_I} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,I} \frac{X_{fjIt_0}}{X_{ft_0}} \log M_{jIt},$$

where $M_{jIt} = \sum_{s \in I} M_{jst}$ measures aggregate imports (excluding France) in destination j for industry I, and $X_{fjIt_0} = \sum_{s \in I} X_{fjst_0}$ is the associated firm-level exports for that industry-destination pair in the initial year t_0. This measure will no longer reflect the cross-firm variation at the detailed product level. However, it captures some potential spillovers across related products in the construction of the demand shock (an increase in export demand for closely related products may induce a firm to direct innovation towards these related products).

Constructing these export demand shocks generates outliers for a few firms that export a small set of products (often highly specialized) to small destinations (such as yachts to Seychelles and Maldives). We therefore trim our sample by removing firms with extreme changes in our con-

calculate destination market shares) as well as production data (so we can calculate export intensity).

[17]Total exports reported by customs and in the production data do not always exactly match, though they are highly correlated. One potential source of difference comes from small exports towards other European Union countries which are not reported in custom data (see Appendix B for more details).

structed export demand. We regress this demand shock on a firm fixed effect and trim observations with a residual that is above/below the 97.5th/2.5th percentile. That is, observations with the largest variations in their export demand shock (relative to their firm mean) are eliminated from our sample.[18]

Before turning to the impact of the export demand shock on the firms' innovation response, we note that this demand shock has a very significant explanatory power for a firm's total export response (see Table B1, which uses a similar estimating strategy as the one we develop in the next section for innovation).

4.2 Innovation measures

We consider three main measures of innovation for each French firm f in any year t. The first measure counts all patent applications filed by the firm during year t. To better reflect the firm's individual contribution, we use fractional counts for patents shared with other firms (so that a patent filed with 2 other applicants counts as a third). The second measure selects higher quality innovations by counting triadic families of patents: when the same innovation (within a patent family) is filed at three different patent offices in Europe (the European Patent Office, EPO), the United States (U.S. Patent Office, USPTO) and at least one of the major Asian economies (Japan, China or Korea).[19] The rationale behind this measure is that the best ideas are more likely to be protected in the three main economic regions worldwide. Another feature of this triadic patent measure is that it is more immune to geographical and institutional biases, i.e. to the possibility that different patent offices would differ with regard to quality standards and/or the enforcement of Intellectual Property Rights (see Park, 2008). When aggregating triadic patent families by firm, we also use fractional counts to reflect a given firm's contribution to the patent family. The third measure counts (fractional) patent applications in Europe (at the EPO) – the main domestic market for French firms. This measure is thus less restrictive than the triadic measure (which requires filing in 3 regions including Europe); but it provides a homogeneous institutional framework for the assessment of intellectual property. Other innovation measures yield similar results (see section 4.5.1). Appendix B provides additional details on the construction of our patent measures.

[18]The incidence of these outliers decreases as we aggregate the trade flows from products to industries. We have experimented with different threshold cutoffs in the 1-5% range. Our qualitative results are robust to these changes (see Table B3 in Appendix C).

[19]This definition is slightly broader than the definition of triadic patent families used elsewhere in the literature as we consider China and Korea in addition to Japan.

4.3 Main estimation strategy

Our baseline regression seeks to capture the impact of the exogenous demand shock on a firm's innovation response. We expect this innovation response to incorporate the cumulated effects of the trade shocks over time. We thus do not use year-to-year differences in the demand shock (first differences) and use that shock as constructed (in "levels") along with a firm fixed-effect in order to capture its within-firm variation (relative to the firm mean over time). We also add sector-time fixed-effects to remove any time variation that is common to the firm's sector. We restrict our analysis to the subset of innovating firms (i.e. firms with at least one patent since 1994).[20]

To capture the indirect competition effect of an export demand shock (which varies with a firm's initial productivity level), we add an interaction between the demand shock and the firm's initial productivity. Just as we did with the firm-level export shares, we only use our initial year t_0 to generate a productivity measure that does not subsequently vary over time $t > t_0$.[21] We assign a 0-9 productivity index d_f to all firms based on their labor productivity (value-added per worker) decile in year t_0 within their 2-digit sector.[22]

The left-hand panel of Figure 7 shows a bin-scatter of our main patent measure (all applications in year t) against the firm's export demand $D_{ft}^{M_s}$ for the same year – absorbing a firm fixed-effect. This clearly shows that there is a very strong correlation between changes in export demand and changes in patent flows (within firms over time); and that a linear relationship provides a very good functional form fit for that correlation. We thus use a linear OLS specification as our baseline regression equation to quantitatively assess this relationship:

$$Y_{ft} = \alpha \ D_{ft} + \beta \ D_{ft} * d_f + \chi_{s,t} + \chi_f + \varepsilon_{ft}, \tag{6}$$

where Y_{ft} is one of our innovation measures based on the flow of patent applications during year t by firm f and D_{ft} is one of our export demand proxies ($D_{ft}^{M_s}$ or $D_{ft}^{M_I}$) for that same year t. Those proxies are constructed so that they are exogenous to the firm's decision in year $t > t_0$.[23]

[20] Investigating the entry margin into - or the exit margin out of - the set of innovating firms is also an important topic, but we leave it for further research.

[21] Recall that t_0 is the first year since 1994 in which the firm reports positive exports. This year is equal to 1994 for about 50% of the firms and is always removed from the estimation.

[22] When a firm belongs to the manufacturing sector for a subset of our sample years, we only use those years in our estimation. For a firm not in our manufacturing sample at t_0, we compute its productivity decile within its previous sector at t_0.

[23] Serial correlation in the innovation shocks could induce some correlation between a firm's export structure a time t_0 (which we use to construct our export demand shock for year t) and the subsequent innovation shock in year t. First, we note that a time-persistent effect in the innovation shock will be captured by the firm fixed-effect. To ensure that our results are not driven by transitory serial correlation, we also experiment with dropping additional

The $\chi_{s,t}$ and χ_f capture the sector-time and firm fixed effects and ε_{ft} is an error term. In most of our regressions, we estimate coefficients and standard errors using a Newey-West estimator for the covariance matrix which allow for heteroskedasticity and autocorrelation in the error terms with a maximum lag of 5 years (see Newey and West, 1987 and Wooldridge, 2010).[24]

While the linear panel fixed effect model is our preferred specification, we also show results from a Poisson model in Table B6 using the following specification:

$$\ln\left(\mathbb{E}\left[\tilde{Y}_{ft}\right]\right) = a\ D_{ft} + b\ D_{ft} * d_f + \chi_{s,t} + \chi_f, \tag{7}$$

where $\tilde{Y}_{ft}$ is a measure of total patent applications that does not use fractional counts and is therefore an integer. We estimate a and b and corresponding standard errors using maximum likelihood.

4.4 Baseline results

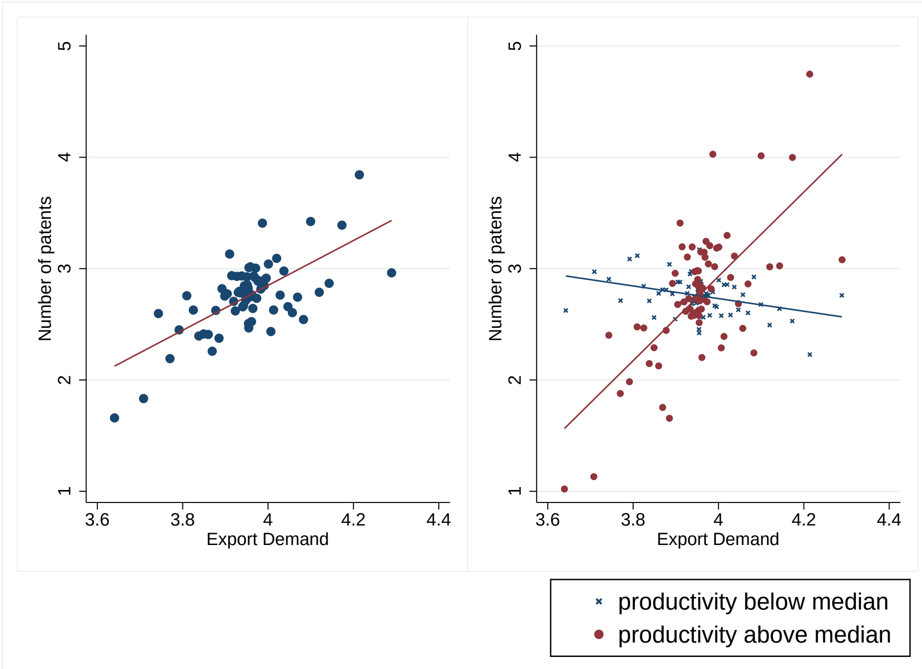
In the model, an increase in market size induces both a positive market size effect and a counteracting competition effect which is most pronounced (and potentially dominant) for the least productive firms (Section 2.6). In the data this feature clearly stands out. Graphically the right-hand side panel in Figure 7 shows that the number of patents increases much more with export demand in firms initially more productive (above the median productivity). Quantitatively Table 4 reports the results from the baseline regression (6). A positive export shock reduces innovation for firms in the lowest productivity decile ($d_f = 0$); the export shock's impact on patenting increases with initial productivity and turns positive at productivity around the third or fourth decile: firms initially more efficient increase more their innovation when they face a positive export shock. This pattern holds for all three patent and two demand shock measures.

Our coefficients from column 1 using the product-level demand shock imply the following quantitative response in the number of patents to the average demand shock: for a firm in the lowest productivity decile, the number of patents (relative to the firm average) is 3.3 patents lower than the sector average; and each additional productivity decile increases this patent response by 0.96 patent. Thus the response of a firm in the top productivity decile amounts to 8.7 more

years of data following t_0. Instead of starting our sample at $t_0 + 1$, we have tried starting at $t_0 + 2$ or $t_0 + 3$. We report those alternative specifications in Table B4, which are qualitatively very similar to our baseline results (even though the sample size is reduced in our critical time dimension).

[24] We also show robustness of our baseline results using standard errors clustered by firm (see Table B5). However, given the relatively long time dimension of our sample, we find this latter specification too conservative and prefer the Newey-West estimator. As argued by Abadie et al. (2017), in such fixed-effect models, clustering standard error only matters if we expect heterogeneity in the treatment effect.

Figure 7: Patenting increases more with demand for initially more efficient firms



Notes: Each dot represents the quantile-average of the residual of the number of patent on a firm fixed effect (y-axis) against the quantile-average of the residual of the demand variable $D_{ft}^{M_s}$ on a firm fixed effect (x-axis), for all firms (left-hand side panel) or for both firms below (blue) or above (red) the productivity median at t_0 (right-hand side panel).

patents than the sector average (still relative to the firm average). Our coefficients when using the industry demand shocks (column 2) yield very similar results.

4.5 Robustness analysis

Our main finding – that initially more productive firms respond to an export demand shock by innovating relatively more – is robust to various alternative specifications. In this subsection, we show the robustness of our main results to: (i) considering other patent indicators; (ii) controlling for firm specific characteristics; (iii) excluding dominant firms in a destination market; (iv) considering alternative measures and heterogeneous effects for a firm's proximity to frontier; and (v) controlling for pre-trends with sector-decile specific time trends.

4.5.1 Other patent indicators

There are many alternative ways of aggregating patent counts, which yield different measurements of a firm's innovation output. In Table 5 we consider 6 alternative measures of Y_{ft} and

Table 4: Baseline results

Dependent variable	All patents		Triadic patents		EPO patents	
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_I}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_I}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_I}$ (6)
Demand	-3.260***	-2.578**	-0.265***	-0.224***	-0.368***	-0.447***
	(1.014)	(1.056)	(0.0786)	(0.0820)	(0.123)	(0.143)
Decile × Demand	0.960***	0.909***	0.0859***	0.0862***	0.125***	0.114***
	(0.255)	(0.304)	(0.0195)	(0.024)	(0.029)	(0.039)
Cutoff decile	4	3	4	3	3	4
Nb of observation	77,901	77,918	77,901	77,918	77,901	77,918
R^2	0.897	0.888	0.759	0.747	0.849	0.836

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Cutoff decile corresponds to the first value of d_f for which the overall effect becomes positive. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

run our baseline model (6) with these new dependent variables. (1) We first restrict our triadic measure to a dyadic one by only considering the number of patent families at the USPTO and at the EPO (dropping Asia); (2) We then expand the definition by counting all patent families (instead of individual patents as in our baseline); (3) We return to a count of individual patents but restrict this to EPO patent applications; (4) We count only the number of priority patent applications; (5) We drop the construction of fractional patent counts ("raw" number of patent); and (6) We only count the number of patent applications that will ultimately be granted in any patent office.[25] The results for all these alternative patent measures are similar to those in our baseline Table 4: the export demand shock has a positive effect on the corresponding measure of innovation in frontier firms but has a negative effect on innovation in lagging firms.

4.5.2 Direct control for firm size

A firm experiencing an increase (decrease) in market size which is not initially related to innovation, may still respond to it by innovating and exporting more (less). We do not control for firm size directly in our baseline as our theoretical model suggests that changes in size that are driven by the export shocks should be incorporated into our measure of the impact of exports on innovation. However, in order to eliminate a direct impact of firm scale on our estimates, we

[25]See Appendix B for additional details on the construction of all these indicators.

Table 5: Alternative ways of counting patents

Dependent variable	Dyadic	Families	EPO*	Prior	Nb Appln	Granted
Demand Measure	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-0.233**	-0.936***	-0.883***	-1.364***	-4.732***	-1.197*
	(0.098)	(0.330)	(0.222)	(0.502)	(1.253)	(0.629)
Decile × Demand	0.072***	0.271***	0.245***	0.408***	1.375***	0.363**
	(0.024)	(0.087)	(0.050)	(0.133)	(0.315)	(0.154)
Nb of observation	77,901	77,901	77,901	77,901	77,901	77,901
R^2	0.819	0.802	0.848	0.830	0.881	0.900

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). See Appendix B for a complete definition of the different indicators used in this Table. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

now include such a control for firm size (at time t). We select different empirical measures of size from the production data: employment, raw materials, net and gross capital stock, and sales. The corresponding regression results are reported in Table 6. They clearly show that a direct control for size does not affect our previously reported baseline coefficients (reported again in column 1): the coefficients remain virtually unchanged. Similar results are obtained when using our two other main measures of innovation (triadic and EPO families) and are available upon request.

4.5.3 Excluding markets where a firm is a leader

When a French firm has a dominant market share in a market (j, s), then the world exports M_{jst} may be correlated with the firm's exports X_{fjst} (even though French exports are excluded from the construction of the world exports M_{jst}) as those other Foreign exporters may respond to actions taken by this French firm. To investigate this further, we drop from our dataset the markets (j, s) (in all years) for a firm f whenever its export sales in market (j, s) are above 10% of world exports (including France) into this market for any given year. These instances represent 6.7% of the customs data observations and predominantly reflect firms exporting to African destinations. The results are reported in Table B7 in the Online Appendix; and once again leave our baseline results virtually unchanged.

Table 6: Control for firm size

Dependent variable	Number of patents					
Demand measure	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-3.260***	-3.434***	-3.285***	-3.218***	-2.799***	-3.280***
	(1.014)	(1.039)	(1.024)	(1.017)	(1.004)	(1.012)
Decile × Demand	0.960***	0.970***	0.954***	0.960***	0.874***	0.976***
	(0.255)	(0.263)	(0.257)	(0.256)	(0.258)	(0.255)
Size		0.696***	1.257***	2.007***	2.007***	1.227***
		(0.114)	(0.096)	(0.201)	(0.350)	(0.187)
Nb of observation	77,901	76,236	76,678	76,860	77,240	77,605
R^2	0.897	0.900	0.898	0.898	0.898	0.898

Notes: This table presents regression results of an OLS estimation of equation 6 where we add a control for firm size. Column 1 uses no control, column 2 controls for the log of raw material inputs, column 3 (resp. 4) controls for the log of net (resp. gross) capital stock, column 5 controls for the log of employment and column 6 controls for the log of sales (we obtain similar results when we control jointly by any subset of these covariates). Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

4.5.4 Other measures of proximity to frontier

So far, our model uses initial productivity deciles to measure a firm's proximity to its sector's technology frontier. We now consider alternative measures for this proximity. Table 7 shows that our baseline results (1) are robust to (2) measuring productivity deciles using sales instead of value added per worker; as well as (3)-(6) measuring proximity to frontier using a binary threshold for initial productivity within sector set at 50%, 75%, 90% and 95%. Those results highlight how the impact of the export shock is magnified for firms very close to the frontier (at the very top of the distribution of initial productivity).[26]

In light of these results, which suggest that the positive effect of export demand on innovation may be concentrated among the most productive firms, we allow our key interaction coefficient β in equation (6) to vary with the productivity decile d_f. Our estimating equation then becomes:

$$Y_{ft} = \sum_{d=0}^{9} \left[\beta_d \ D_{ft} * \mathbb{1}_{d_f=d}\right] + \chi_{s,t} + \chi_f + \varepsilon_{ft}, \tag{8}$$

[26]Similar results are obtained when using Triadic and EPO families. Tables are available upon request to the authors.

Table 7: Alternative definition of frontier

Dependent variable	Number of patents					
Demand measure	$D_{ft}^{M_s}$ (1)	$D_{ft}^{M_s}$ (2)	$D_{ft}^{M_s}$ (3)	$D_{ft}^{M_s}$ (4)	$D_{ft}^{M_s}$ (5)	$D_{ft}^{M_s}$ (6)
Demand	-3.260***	-1.316	-1.042**	-0.0904	0.520	0.578
	(1.014)	(0.890)	(0.501)	(0.680)	(0.699)	(0.671)
Interaction	0.960***	0.578**	4.438***	5.456***	8.375**	16.63**
	(0.255)	(0.235)	(1.117)	(1.835)	(3.570)	(7.276)
Nb of observation	77,901	77,901	77,901	77,901	77,901	77,901
R^2	0.905	0.905	0.905	0.905	0.905	0.906

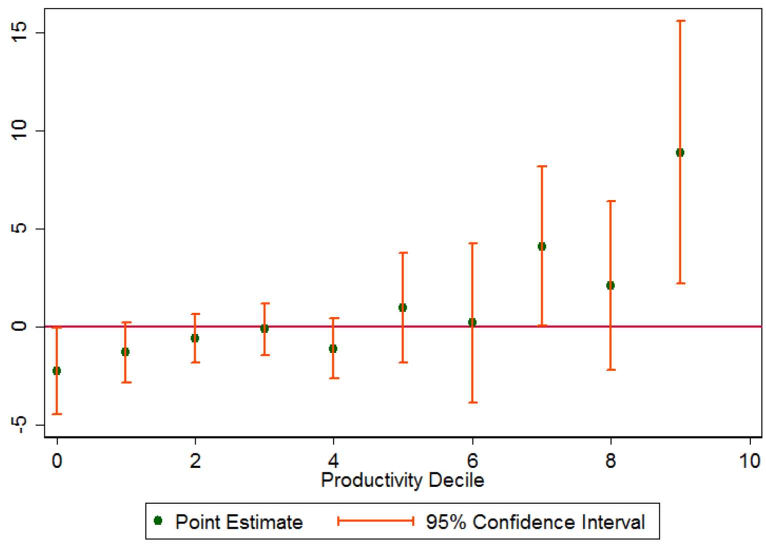
Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1) Column (1) is our baseline model, column (2) defines productivity using sales instead of value added, columns (3) to (6) no longer construct decile groups but use a dummy variable for being above the sectoral 50^{th}, 75^{th}, 90^{th} and 95^{th} percentile of the initial productivity distribution. This dummy is interacted with the demand variable. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

where $\mathbb{1}_{d_f=d}$ are indicator dummies for each productivity decile. This new specification allows us to relax the assumption that there is a constant slope shift across decile groups and to account for potential non linear effects of our export demand shock variable for different levels of productivity. Coefficients and corresponding confidence intervals are graphically reported in Figure 8. They show that the assumption of a constant effect across decile group is a good approximation – with the possible exception of the top-decile where the effect is magnified relative to the linear trend (this confirms the results from Table 7). This figure also highlights that the effect of the demand shock is clearly negative for some of the lowest productivity deciles; and that this effect turns positive for all deciles above the median (deciles 5 through 9). The confidence intervals remain relatively wide since those decile indicators induce substantial collinearity.

4.5.5 Controlling for sector-decile specific time trends

To deal with the possibility that firms in different productivity deciles and different sectors may evolve differently over time and in particular may follow different innovation trends independently from the export demand shock, we add dummies for all year-productivity decile bins. Those results are reported in the odd-numbered columns (1), (3), (5) in Table 8. In addition, we also consider dummies for the triple interaction of all year-sector-productivity decile bins. Those results are reported in the even-numbered columns (2), (4), (6). This sectoral classification is the same

Figure 8: Response to Demand by decile of productivity



Notes: Regression coefficients are estimated using a panel fixed effect estimator and corresponding 95% confidence intervals are constructed with Newey-West estimated standard errors of equation (8).

that we use to construct the productivity deciles – which are now orthogonal to any sector-level changes over time. Table 8 highlights that these controls do not change the message from our baseline results (though the negative impact for low productivity firms is no longer significant for the case of EPO patent families).

4.6 Extensions

In this last section, we extend our empirical analysis in different directions. First, we categorize export destinations based on a separate measure of competition in those destinations and show that the competition effect is most salient in high competition export destinations. We then show how we obtain similar results with an alternate specification based on long time-differences (splitting our sample years into two intervals). This provides an alternate way of capturing the slow-moving changes in the variables of interest (changes in export demand and the associated innovation response). And third, we contrast our main results using measures of innovation output (patents) with results obtained with measures of innovation inputs (R&D inputs) – which are available for a subsample of firms in our sample.

Table 8: Decile group specific evolution

Dependent variable	All patents		Triadic patents		EPO patents	
Demand measure	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-2.876***	-2.135**	-0.179**	-0.135**	-0.168	-0.0755
	(0.975)	(0.868)	(0.0716)	(0.0638)	(0.121)	(0.120)
Decile × Demand	0.900***	0.727***	0.0689***	0.0515***	0.0833***	0.0614**
	(0.267)	(0.251)	(0.0200)	(0.0188)	(0.0316)	(0.0309)
Nb of observations	77,901	77,744	77,901	77,744	77,901	77,744
R^2	0.897	0.899	0.759	0.763	0.849	0.849

Notes: This table presents regression results of an OLS estimation of equation 6, to which a productivity decile × year fixed effect is added (columns 1, 3 and 5) or replacing the sector × time fixed effect with a sector × productivity decile × time fixed effect (columns 2, 4 and 6). Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

4.6.1 Direct competition effect

We now highlight how the skewed response of innovation to the export shock is driven by the induced competition effect (a demand-side explanation) – as opposed to supply-side effects (such as skewness in the costs or returns to R&D). Towards this end, we use an index of market competition from Djankov et al. (2002) to separate all French export market destinations into high- and low- competition categories. These data on competition levels across countries are now regularly updated and reported in the World Bank's "Doing Business" database. There are several different measures for competition; we use the index reflecting the ease of opening up a business in a country. This generates a time-invariant index by destination on a 0-100 scale.[27]

We then separate destinations into high (H, above median) and low (L, below median) competition according to this index and construct two separate export demand shock measures for those two categories:

$$D_{ft,H}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \mathbb{1}_{C_j > \hat{C}_t} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst},$$

and

$$D_{ft,L}^{M_s} = \frac{X_{ft_0}^*}{S_{ft_0}^*} \sum_{j,s} \mathbb{1}_{C_j \leq \hat{C},t} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst},$$

[27]See Appendix B for more details about these data and for an explanation on why we can only construct a time-invariant measure of competition by country.

where C_j denotes the country-specific competition index (ease of doing business) and $\hat{C}_t$ is the median of this value in year t. Hence $\mathbb{1}_{C_j \leq \hat{C}_t}$ is equal to 1 if country j is less competitive than the median country. These two new demand shocks sum up to our baseline measure $D_{ft}^{M_s}$ and capture separate export demand proxies for destinations with high/low competition.

We then estimate the following model:

$$Y_{ft} = \alpha_H \ D_{ft,H}^{M_s} + \beta_H \ D_{ft,H}^{M_s} * d_f + \alpha_L \ D_{ft,L}^{M_s} + \beta_L \ D_{ft,L}^{M_s} * d_f + \chi_{s,t} + \chi_f + \varepsilon_{ft}. \tag{9}$$

Our theory predicts that we should observe the skewness impact of the demand shocks more (or entirely) for the high-competition destinations. The results reported in Table 9 strongly confirm this prediction. This table considers two separate ways of measuring the threshold value $\hat{C}$. In the odd-numbered columns (1), (3), (5), $\hat{C}$ is the yearly median value once the measure of competition has been aggregated by product (i.e. on a sample containing one observation per product/firm). In the even-numbered columns (2), (4), (6), we use the threshold value when we keep only one observation per country. Both threshold measures for high/low competition confirm that the skewness effect is predominantly driven by the impact of export demand in high competition destinations.

4.6.2 Regression in long differences

In this section, we explore an alternate estimation strategy based on long differences over time. We decompose our full 1995-2012 sample into two periods $p \in \{p_0, p_1\}$ of equal length. Our demand variable is then measured in log differences, at the product (6 digit HS) or industry (3 digit ISIC) level, as:

$$\Delta D_f^{M_s} = \frac{X_{fp_0}^*}{S_{fp_0}^*} \sum_{j,s} \frac{X_{fjsp_0}}{X_{fp_0}} \log \frac{M_{jsp_1}}{M_{jsp_0}},$$
$$\Delta D_f^{M_I} = \frac{X_{fp_0}^*}{S_{fp_0}^*} \sum_{j,I} \frac{X_{fjIp_0}}{X_{fp_0}} \log \frac{M_{jIp_1}}{M_{jIp_0}},$$

where all trade flows are aggregated over each period p_0 and p_1.[28] Similarly, we measure innovation output ΔY_f as the difference in patent introductions between both periods (same measures as for our baseline analysis).

[28] $X_{fjsp_0} = \sum_{t \in p_0} X_{fjst}$, and $X_{fp_0} = \sum_{j,s} X_{fjsp_0}$. $X_{fp_0}^*$ and $S_{fp_0}^*$ are the average over period p_0 of yearly (Ficus) exports and sales. M_{jsp} is the average over period p of M_{jst}. If $M_{jsp} = 0$, we replace it with 1 euro. The construction is similar at the industry level. Finally, d_{fp_0} is the decile of the average (within sector) productivity decile over period p_0. A firm's sector is its most representative one during period p_0.

Table 9: More direct estimation of the competition effect

Dependent variable	All patents		Triadic patents		EPO patents	
Demand Measure	$D^{M_s}_{ft,H}$,	$D^{M_s}_{ft,L}$	$D^{M_s}_{ft,H}$,	$D^{M_s}_{ft,L}$	$D^{M_s}_{ft,H}$,	$D^{M_s}_{ft,L}$
	(1)	(2)	(3)	(4)	(5)	(6)
Low Competition	-0.030	-0.113	-0.026	-0.041	-0.147	-0.140
	(0.457)	(0.465)	(0.031)	(0.032)	(0.092)	(0.092)
High Competition	-5.686***	-5.275***	-0.373**	-0.387**	-0.691***	-0.902***
	(1.980)	(1.769)	(0.153)	(0.151)	(0.222)	(0.221)
Interact. Low	0.086	0.008	0.012	0.013**	0.024	0.001
	(0.144)	(0.086)	(0.009)	(0.006)	(0.029)	(0.014)
Interact. High	2.134***	1.338**	0.182***	0.103**	0.306***	0.179***
	(0.652)	(0.522)	(0.052)	(0.043)	(0.084)	(0.059)
Nb of observation	76,821	76,821	76,821	76,821	76,821	76,821
R^2	0.892	0.896	0.836	0.756	0.861	0.843

Notes: This table presents regression results of an OLS estimation of equation (9). Demand (low comp.) corresponds to $D^{M_s}_{ft,B}$ as defined in section 4.6.1 and Demand (high comp.) to $D^{M_s}_{ft,A}$. Interaction low comp. (resp high comp.) is defined as the interaction between the productivity decile of the firms and $D^{M_s}_{ft,B}$ (resp $D^{M_s}_{ft,A}$). Columns 1, 3 and 5 define the competition median at the firm × product level each year to compute demand shocks while columns 2, 4 and 6 compute the median at the country level (see section 4.6.1). Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

The firm fixed-effect is differenced-out but we keep the sector fixed effect; and we add the firm's productivity decile as an additional (pre-trend) control. Our estimating equation then becomes:

$$\Delta Y_f = \alpha \ \Delta D^{M_s}_f + \beta \ \Delta D^{M_s}_f * d_{fp_0} + \gamma \ d_{fp_0} + \chi_s + \varepsilon_f, \tag{10}$$

The results are reported in Table 10. The impact of the demand shock for the lowest productivity decile is still negative though barely significant. However, the interaction between the demand shock and the firm's initial productivity decile is positive and much more strongly significant. These results confirm our previous baseline findings.

4.6.3 Measures of innovation inputs: R&D investment

Up to now, we have used measures for the output of innovation based on patents. Another commonly used measure for innovation is based on R&D investment (the inputs for the innovation

Table 10: Long Difference regressions

Dependent variable	Nb patents	Triadic families	EPO families
Demand Shock	$\Delta D_f^{M_s}$	$\Delta D_f^{M_s}$	$\Delta D_f^{M_s}$
	(1)	(2)	(3)
Demand	-5.382**	-0.314*	-0.514*
	(2.431)	(0.191)	(0.302)
Decile × demand	1.260**	0.108**	0.140**
	(0.562)	(0.0461)	(0.0612)
Decile	-0.0345	-0.00493	0.00832
	(0.0554)	(0.00356)	(0.00661)
Nb of observation	4,707	4,707	4,707
R^2	0.0197	0.0171	0.0138

Notes: This table presents regression results of an OLS estimation. Sample includes one observation per manufacturing firm with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). 1995-2012 is broken down in 2 periods (1995-2003 and 2004-2012), over which trade flows and firm characteristics are aggregated. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

process). As with any input-based measure, the latter generates biases against firms that use those inputs more efficiently to generate innovation. A separate issue is that this measurement of R&D inputs is only available based on survey responses covering a subsample of firms. The sample is exhaustive for the largest innovators, but the sampling frequency decreases steeply with firm size. Thus, smaller firms are not consistently surveyed over time, thwarting the construction of time-varying measures of innovation (see more details in Appendix B.6).

Table 11 reports the correlations between our three main patent measures and a firm's total R&D budget and the associated number of R&D researchers – whenever this survey data is available. The left-hand side panel reports the between-firm correlations based on firm averages across years. Although the correlations across innovation inputs (R&D) and outputs (patents) in the bottom-left rectangle are weaker than the correlations within a set of inputs or outputs, the between firm correlations are nevertheless substantial and highly significant. However, those correlations between inputs and outputs drop precipitously when focusing on within-firm variations – whereas the correlations within the set of either inputs or outputs remain strong. Those correlations are reported in the middle and right-hand side panels in Table 11. (The middle panel reports within-firm correlations across all years after absorbing a firm fixed-effect; while the right-hand side panel reports the within-firm correlation between periods p_0 and p_1 as defined in our

Table 11: Correlations between R&D and patent measures of innovation

Between

	Nb patents	Triadic families	EPO families	R&D budget	Nb researchers
Nb patents	1.00				
Triadic families	0.95	1.00			
EPO families	0.97	0.91	1.00		
R&D budget	0.47	0.44	0.51	1.00	
Nb researchers	0.46	0.40	0.52	0.91	1.00

Within

	Nb patents	Triadic families	EPO families	R&D budget	Nb researchers
Nb patents	1.00				
Triadic families	0.51	1.00			
EPO families	0.68	0.36	1.00		
R&D budget	0.09	0.01	0.07	1.00	
Nb researchers	0.08	0.04	-0.02	0.59	1.00

Long Difference

	Δ Nb patents	Δ triadic fam	Δ EPO fam	Δ R&D budget	Δ Nb researchers
Δ Nb patents	1.00				
Δ triadic fam	0.78	1.00			
Δ EPO fam	0.69	0.34	1.00		
Δ R&D budget	0.11	0.05	0.03	1.00	
Δ Nb researchers	0.07	0.13	-0.08	0.54	1.00

Notes: This table presents the pairwise correlations between innovation measures from PATSTAT and from the R&D survey. It is based on the sample of manufacturing firms with at least one patent in 1995-2012, for which we can compute the export demand shock (see section 4.1). Between correlations are the correlations between the firms' averages over the period. Absorbing a year or year x sector fixed effect prior to taking the firms' average leaves the correlations and their p-values virtually unchanged. Within correlations are the correlations after taking out the firm fixed effect. The long difference correlations are the correlations between the period 1 innovation measures. Using Sidak-adjusted p-values, all the correlations are significant at 5%, except the within and LD correlations between triadic families and total R&D budget and the LD correlation between EPO families and total R&D budget.

previous long-difference regressions.) Those very low correlations could be driven by the fact that R&D investments within a firm occur at discrete time intervals and slowly translate into increased patents – along with unmeasured changes in the efficiency/utilization of those R&D inputs.

In Table 12, we report the regression results for both our baseline specification as well as the long-difference one using both R&D input measures. In order to separate out the impact of the reduction in sample size associated with the availability of R&D data, we report results using our main patent innovation output variable with the same subsample of firm-years. In the left-hand columns reporting the level regressions, we see that the reduction in sample size does not affect our main results for the skewness impact of the export demand shock on the patent response. The coefficients using the R&D inputs have the same signs, but are not significant. We conjecture that this is due to the fact that the patent measure better captures the within-firm changes in innovation intensity at a yearly frequency. This is confirmed by the results for long-differences, where the coefficients for the R&D inputs are now substantially stronger and significant for the case of the number of researchers. As was the case in our full sample, the significance of the patent response is reduced when moving to the long-difference specification. In this case with a much smaller sample, those coefficients for the patent response are no longer significant.

Table 12: R&D SURVEY

Dependent variable	Regression in levels			Regression in long differences		
Innovation measure	R&D budget (1)	Nb researchers (2)	Nb patents (3)	ΔR&D budget (4)	ΔNb researchers (5)	ΔNb patents (6)
Demand	-1441.1	-17.67*	-8.859***	-4228.2	-34.01**	-6.506
	(3015.6)	(9.531)	(3.340)	(4279.9)	(15.03)	(4.242)
Decile × Demand	1072.7	4.181*	2.219***	1541.8	8.554**	1.560*
	(720.5)	(2.321)	(0.714)	(1048.4)	(3.438)	(0.823)
Decile				-97.65	0.657	0.0835
				(173.3)	(0.568)	(0.102)
Nb of observations	20,030	20,662	21,480	1,746	1,713	1,827
R^2	0.918	0.844	0.896	0.0112	0.0288	0.0301

Notes: This table presents regression results of an OLS estimation of equation 6 (columns 1-3) and 10 (columns 4-6). Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1); the sample is further reduced to pairs (firm, year) in the R&D survey (columns 1-3) or to firms surveyed at least once in p_0 and p_1 in the R&D survey (columns 4-6). For the regressions in levels, coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

5 Conclusion

In this paper we analyzed the impact of export shocks on innovation for French firms. On the one hand those shocks increase market size and therefore innovation incentives for all firms. On the other hand they increase competition as more firms enter the export market. This in turn reduces profits and therefore innovation incentives particularly for firms with low initial productivity. Overall an export demand shock has a more positive effect on innovation in high productivity firms, whereas it may negatively affect innovation in low productivity firms. We tested this prediction with patent, customs and production data covering all French firms. To address potential endogeneity issues, we constructed firm-level variables which respond to aggregate conditions in a firm's export destinations but are exogenous to firm-level decisions. We showed that patenting robustly increases more with demand for initially more productive firms. This effect is reversed for the least productive firms as the negative competition effect dominates. Moreover, we showed that the positive interaction between a firm's initial productivity and the export demand shock is primarily driven by those export destinations where product market competition is highest. This further confirms the fact that export demand shocks involve both, a market size and a competition effect for French manufacturing innovators.

Our analysis can be extended in several directions. A first direction will be to use the same data to explore the effect of imports on innovation, using the same comprehensive databases. This would allow us to better understand why Bloom et al. (2016) and Autor et al. (2016) get opposite conclusions. A second direction would be to look at the impact of exports on the citations to previous innovations, thereby shedding new light on the knowledge spillover effects of trade. These await future research.

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Online Appendix for
"The Impact of Exports on Innovation: Theory and Evidence"

A Theoretical Appendix

A.1 Proof of Proposition 1

Uniqueness: in the $(\widehat{C}_D, \lambda)$ space, one can show that the (ZCP) condition is strictly downward-sloping while the (FE) condition is strictly upward-sloping, ensuring uniqueness of the equilibrium if such an equilibrium exists. More precisely: (a) an increase in competition from λ to $\lambda + d\lambda$ reduces the profit of firms with baseline cost $\widehat{C}_D(\lambda)$, so that those firms no longer operate; this means that $\widehat{C}_D(\lambda + d\lambda) < \widehat{C}_D(\lambda)$, which proves that the (ZCP) curve is strictly downward-sloping; (b) an increase in competition from λ to $\lambda + d\lambda$ reduces the profit of all firms (the envelope theorem ensures that at the optimal innovation level $\frac{\partial \Pi}{\partial k} = 0$ so that $\frac{d\Pi}{d\lambda} = \frac{\partial \Pi}{\partial \lambda} < 0$); this in turn means that $\widehat{C}_D$ has to strictly increase for the (FE) condition to hold, which proves that the (FE) curve is strictly upward-sloping.

Existence: to prove the existence of an equilibrium, we show that the (FE) curve lies below the (ZCP) curve for values of $\widehat{C}_D$ close to $\tilde{c}_{0D}$, and that the (FE) curve ends up above the (ZCP) curve for high values of $\widehat{C}_D$. As $\widehat{C}_D$ becomes close to $\tilde{c}_{0D}$, (ZCP) implies a value for λ which is positive and bounded away from zero, whereas (FE) requires λ to become arbitrarily small, because the integrand must go to $+\infty$ for the integral over a very small interval to remain equal to F_D^E. Next, recall that the (ZCP) curve must remain below the $\lambda = \frac{\alpha}{\widehat{C}_D}$ curve. Given that $\frac{\alpha}{\widehat{C}_D} \longrightarrow 0$ when $\widehat{C}_D \longrightarrow +\infty$, the $\frac{\alpha}{\widehat{C}_D}$ curve must cross the (FE) curve at some point. At this point, the (ZCP) curve lies below the (FE) curve.

A.2 Proof of Proposition 4

Proof. The first part of proposition 4 follows directly: for a given distribution of French firms Γ and a given market size L in destination D, one can find c_I and F small enough such that $\overline{C} < \widehat{C}_I < \widehat{C}$, with $\overline{C}$ such that $\frac{dQ}{dL}(\overline{C}) = 0$. Importantly, the limit cases with $c_I = 0$ or $F = 0$ have a solution, which ensures that we can choose c_I and F as small as possible to obtain a solution verifying $\overline{C} < \widehat{C}_I < \widehat{C}$. When $c_I = 0$, all firms innovate, because the first unit of innovation has a zero cost. When $F = 0$ there is no operating cost, so that all firms with positive output actually produce.

Formally and after some algebra, we have:

$$\begin{aligned}
\overline{C} < \widehat{C}_I \quad &\Leftrightarrow \quad \frac{2\beta c_I}{\varepsilon\alpha L} < \frac{\frac{L}{\lambda}\frac{d\lambda}{dL}}{1+\frac{L}{\lambda}\frac{d\lambda}{dL}} \\
\widehat{C}_I < \widehat{C} \quad &\Leftrightarrow \quad F < \frac{c_I^2}{\beta\varepsilon^2 L\lambda},
\end{aligned}$$

Because the elasticity of competition with respect to the market size exists when $c_I = 0$ and is positive (it is the ratio of the average profits over the average revenues, see below), we can choose c_I small enough that $\overline{C} < \widehat{C}_I$. Then and because λ exists and is strictly positive when $F = 0$, we can choose F small enough that $\widehat{C}_I < \widehat{C}$.

The second part is detailed below.

Differencing (FE) with respect to L yields:

$$\begin{aligned}
&\int_{\tilde{c}_{0D}}^{\widehat{C}_D} \pi d\Gamma_D(\tilde{c}) = -L\int_{\tilde{c}_{0D}}^{\widehat{C}_D} \frac{\partial\pi}{\partial\lambda}\frac{d\lambda}{dL} d\Gamma_D(\tilde{c}) \\
\Rightarrow &\frac{d\lambda}{dL}\frac{L}{\lambda} = \frac{\int_{\tilde{c}_{0D}}^{\widehat{C}_D} \pi d\Gamma_D(\tilde{c})}{\int_{\tilde{c}_{0D}}^{\widehat{C}_D} r d\Gamma_D(\tilde{c})} = \beta\frac{\int_{\tilde{c}_{0D}}^{\widehat{C}_D} q^2(\tilde{c},k;\lambda) d\Gamma_D(\tilde{c})}{\int_{\tilde{c}_{0D}}^{\widehat{C}_D} q(\tilde{c},k;\lambda)\left[\alpha - \beta q(\tilde{c},k;\lambda)\right] d\Gamma_D(\tilde{c})}.
\end{aligned}$$

Innovation – or equivalently output or output holding k fixed – decreases for the marginal innovator if and only if $\frac{d\lambda}{dL}\frac{L}{\lambda} > \frac{\alpha - \widehat{C}_I\lambda}{\widehat{C}_I\lambda}$ (see equation (4)). Using the above value for the elasticity of competition with respect to market size and after some algebra, output decreases for the marginal innovator if and only if:

$$\int_{\tilde{c}_{0D}}^{\widehat{c}_D} \left[q(\tilde{c},k;\lambda) - \frac{2c_I}{\varepsilon L}\right] q(\tilde{c},k;\lambda) d\Gamma_D(\tilde{c}) > 0. \tag{11}$$

Given that $q(\widehat{C}_I, k; \lambda) = \frac{c_I}{\varepsilon L}$, the distribution Γ_D must put enough weight on local firms with output above twice the output of the marginal innovator. ■

B Data description

B.1 Patent data

Our first database is `PATSTAT Spring 2016` which contains detailed information about patent applications from every patent office in the world. Each patent can be exactly dated to the day of application, which is sometimes referred to as the "filing date".

Counting patent applications Each French firm is associated with a number of patent applications by that firm each year (see section B.4). If the firm shares a patent with another firm, then we only allocate a corresponding share of this patent to the firm. This raises the well-documented issue of truncation bias Hall et al. (2005). Indeed as we come closer to the end of the sample, we observe a smaller fraction of all patents since many of them are not yet granted [1] In addition, there is a legal obligation to wait 18 months before publication in `PATSTAT`. With our version of Spring 2016 this implies that we can assume the data to be reasonably complete up to 2012. The sector-time fixed effects also deal with the truncation bias in our regressions. An alternative solution could be to use the year of granting instead of the year of application. However, the former is less relevant than the latter as it is affected by administrative concerns and also by potential lobbying activities that have little to do with the innovation itself. In order to be as close to the time of the innovation as possible, we follow the literature and consider the filing date. We consider every patent owned by a French firm, regardless of the patent office that granted the patent rights. Here we need to be aware of the differences in regulations across intellectual property offices. Some patent offices, especially those of Japan and Korea, offer less breadth to a patent, which implies that more patents are needed to protect a given invention than in other patent offices (see de Rassenfosse et al., 2013). Since we only consider French firms, this would become an issue only if some French firms patent a lot in countries like Japan or Korea, in which case the number of patents by such firms would be artificially large. To check that this problem does not drive our results, we build different measures of patent counts as detailed below.

Different counts of patents The various indicators from `PATSTAT` used in the regressions are described in detail below. All these indicators, based on different ways of counting or selecting patents, have pros and cons and shed a different light on our analysis. As stated by de Rassenfosse et al. (2013), it is virtually impossible to define a measure of innovation based on patents that is immune to the various biases that are associated with such data.

Following the innovation literature, we always only select patents of invention (the bulk of patents), thus dropping utility model and design patents.

- `Number of patents`: Each year, we sum over the patents filed by a firm f. When a patent has other applicants than f, we only count the share that f represents among all the co-

[1] The time between patent application and patent granting is a little more than 2 years on average but the distribution of this lag is very skewed with few patent applications still waiting for patent granting many years after the application.

applicants (one third if f has 2 other applicants). This variable thus is a fractional count, as most of the variables shown in the regressions.

- `Triadic families`: when the same invention is filed in different patent offices, in practice the firm typically files for a different patent at each office, each referring to the first it has filed (called priority patent): these patents relate to each other, they belong to the same (DOCDB) family.[2]. Triadic families refer to such families with at least one patent filed at the EPO, one patent filed at the USPTO, and one patent filed at either the Japanese, the Chinese or the Korean Patent Office. We want to select innovations filed in the 3 main economic regions worldwide (Europe, USA and Asia). We depart slightly from the literature regarding the treatment of Asia: we do not want to consider Japan as the only relevant country, but instead add the two main other innovating countries, China and Korea. Finally the family is weighted with how much f contributes to it: $\frac{\sum_{k \text{ patents} \in \text{ family}} \frac{\mathbb{1}_{\text{f is applicant of } k}}{\text{nb applicants}_k}}{\text{nb patents in the family}}$. The date of the family corresponds to the earliest filing year of the patents in this family.

- `EPO families`: The construction is very similar to that of the triadic families, except that the family will be taken into account if there is at least one patent in it filed at the EPO.

- `Dyadic families`: The construction is very similar to that of the triadic families, except that the family will be taken into account if there is at least one patent in it filed at the EPO, and another filed at the USPTO.

- `Families`: The construction is very similar to that of the triadic families, except that we take into account all the families containing a patent applied for by f.

- `EPO*`: We use the fractional count of the patents filed by firm f at the EPO.

- `Raw number of patents`: we use the (non-fractional) count of the number of patents filed by firm f.

- `Only Granted`: We use the fractional count of the granted patents filed by firm f.

[2]The `PATSTAT` data catalog states that "a large DOCDB family might indicate that the applicant seeks a wide geographical protection for the invention", and that "if two applications claim exactly the same prior applications as priorities (these can be e. g. Paris Convention priorities or technical relation priorities [...], then they are defined by the EPO as belonging to the same DOCDB simple family."

B.2 Firm-level accounting data

Our second data source provides us with accounting data for French firms from the DGFiP-INSEE, this data source is called `FICUS` and `FARE`. The corresponding data are drawn from compulsory reporting of firms and income statements to fiscal authorities in France. Since every firm needs to report every year to the tax authorities, the coverage of the data is all French firms from 1994 to 2012 with no limiting threshold in terms of firm size or sales. This dataset provides us with information on the turnover, employment, value-added, the four-digit sector the firm belongs to . . . This corresponds to around 47 million observations and the number of observations per year increases from 1.9m to 3.9m over the period we consider.

The manufacturing sector is defined as category C of the first level of the NAF (*Nomenclature d'Activits Franaise*), the first two digits of which are common to both NACE (Statistical Classification of Economic Activities in the European Community) and ISIC (International Standard Industrial Classification of All Economic Activities). Insee provides each firm with a detailed principal activity code (APE) with a top-down approach: it identifies the 1-digit section with the largest value added. Among this section, it identifies the 2-digit division with the largest value-added share, and so on until the most detailed 5-digit APE code (INSEE (2016)). It is therefore possible that another 5-digit code shows a larger value-added share than the APE identified, but one can be sure that the manufacturing firms identified produce a larger value-added in the manufacturing section than in any other 1-digit section, which is precisely what we rely on to select the sample of most of our regressions. The 2-digit NAF sector, which we rely intensively on for our fixed effects, then represents the most important activity among the main section of the firm. Employment each year is measured on average within the year and may therefore be a non-integer number.

A unique 9-digit identifier called *Siren number* is associated to each firm, this number is given to the firm until it disappears and cannot be assigned to another firm in the future. When a firm merges with another firm, or is acquired by another firm, or makes significant changes in its organization, this number may change over time. Hence, new entrant *Sirens* in our database do not necessary correspond to new firms.

B.3 Trade data

Customs data for French firms Detailed data on French exports by product and country of destination for each French firm are provided by the French Customs. These are the same data as in Mayer et al. (2014) but extended to the whole 1994-2012 period. Every firm must report its exports by destination country and by very detailed product (at a level finer than HS6). However administrative simplifications for intra-EU trade have been implemented since the Single Market, so that when a firm annually exports inside the EU less than a given threshold, these intra-EU flows are not reported and therefore not in our dataset. The threshold stood at 250 000 francs in 1993, and has been periodically reevaluated (650 000 francs in 2001, 100 000 euros in 2002, 150 000 euros in 2006, 460 000 euros in 2011). Furthermore flows outside the EU both lower than 1 000 euros in value and 1 000 kg in weight are also excluded until 2009, but this exclusion was deleted in 2010.

Country-product bilateral trade flows CEPII's database `BACI`, based on the UN database `COMTRADE`, provides bilateral trade flows in value and quantity for each pair of countries from 1995 to 2015 at the HS6 product level, which covers more than 5,000 products. To convert HS products into ISIC industries we use a United Nations correspondence table (when 1 HS code corresponds to 2 ISIC codes, we split the HS flow in half into each ISIC code).

B.4 Matching

Our paper is the first to merge those three very large - patent, administrative, and customs - datasets covering exporting French firms. Merging administrative firm-level data from FICUS/FARE and Customs data is fairly straightforward[3] as a firm can be identified by its *Siren* identifier in both datasets. Thus the main challenge is to match either of these two datasets with `PATSTAT`. Indeed, `PATSTAT` only reports the name of the patent owner. Not only can this name be slightly different from the name reported in the other two databases, but it may also change over time, for example because of spelling mistakes. We thus relied on the work of Lequien et al. (in progress) who developed a matching algorithm to map patents with the corresponding French firms. The advanced methodology, described below, is a leap forward compared with other methods proposed by the literature.

Lequien et al. (in progress) proceed in three main steps to merge `PATSTAT` and `SIRENE`:

1. For each *Siren* number from `SIRENE`, find a small subset of applicant firms in Patstat with phonetic similarities:
    - perform cleaning, splitting and phonetic encoding on firms' name in both databases. Too common words are deleted (THE, AND, CO, FRANCAISE ...).

[3] Although one must keep track of the different definitions of firms across these two datasets.

- sort each name by least frequent encoding in `SIRENE`. The more often a word appears in the database, the less information it can convey to identify firms.
- for each `SIRENE` firm, the first (ie least frequent) cleaned word of the firm's name is compared with every `PATSTAT` name. All the `PATSTAT` names containing this word form a first subset of possible matches. Then the second word of the firm's name is compared with every name in this subset, reducing it further. This procedure stops before arriving at a null subset, and yields a set of likely `PATSTAT` matches for each `SIRENE` name. Very often this set is null because the majority of firms do not patent. On average, this subset contains 10 applicants, reducing a lot the computationally intensive comparisons.

2. Computation of parameters on these possible matches
   - Comparison of the names (raw names, and cleaned names), using Levenshtein distances and an inclusion parameter (all the words in one name are included in the name from the other database)
   - zip code comparison (*code postal*)
   - date comparisons (a firm cannot have patented before its creation)
3. Matching with supervised learning
   - Sample from INPI (*Institut National de la Propriété Intellectuelle*) with 15,000 true matches between *Siren* number and `PATSTAT` *person id* (and in total 170,000 pairs, with the corresponding known mismatches).
   - This sample is randomly split into a learning sample and a verification sample (this procedure is repeated 10 times, and the recall and precision measures are averaged over them, so that the choice of the sample does not alter the results). This allows to choose the relevant variables and estimate the parameters.
   - apply this model on all the possible matches identified in the previous step.
   - in 90% of cases, unique matching. In the remaining 10% of cases, filter further with a decision tree (is the date of creation of the firm lower than the first filing of the applicant?, which couple has the minimum Levenshtein distance between raw names, between cleaned names, is one of the names included in the other?, which firm has the maximum number of employees?)

The recall rate (share of all the true matchings that are accurate) is at 86.1% and the precision rate (share of the identified matches that are accurate) is at 97.0%.

B.5 Other data

We also use additional databases at the country level for our analysis. First we use the October 2015 vintage of the IMF's `World Economic Outlook` which provides country information such as GDP and population with a coverage as wide as possible. Second, to measure the level of competition for each country, we use the "Doing Business" project, based on the work of Djankov et al. (2002) and updated by the World Bank. Among all the available information, we consider the "ease of starting a business" which is the variable with the largest spatial coverage. This is a rating of all country for 0 to 100 that measures the constraints when one want to open a new company in the country. Because most countries are not surveyed each year, we choose to take a time invariant average value of this measure as our competition indicator.

B.6 R&D survey variables and sample

B.6.1 The survey

The annual survey on R&D expenses in firms exists since 1963. It describes the private sector R&D in terms of financial means (spending and financing) and mobilized workers. It covers firms established in France and doing R&D, and gathers information on previous year R&D activities. Usually surveys on firms are sampled with the *rpertoire Sirene*, but this database has no information on R&D activities to select firms that one would like to cover. firms with R&D activities represent 1/200 among active firms in *Sirene*.

The Ministry of Higher Education and Research therefore selects firm according to the following procedure:

1. **The historical repertoire**: All units having had a R&D activity are considered. This repertoire is updated with the newest information from the previous survey: takeover, absorption ... Firms answering they do not do R&D the year of survey but they might do some the following year are kept in this sample.
2. **External sources**: Administrative files and surveys allow to detect new firms possibly doing R&D: firms receiving the *Crdit Impt Recherche*, having the *young innovating firm* status, receiving help from firms incubators, firms reporting R&D activities in other surveys (Community Innovation Survey ...)
3. **Updating with Sirene cessations**: Firms known as having shut down in *Sirene* are eliminated.

4. **Stratification**:

    - Firms with internal spending of R&D over 400 000 are exhaustively interrogated (and above 2 million , they fill a bigger questionnaire).
    - New firms (CIR, JEI ...) are exhaustively interrogated as well (but only since 2001, see below).
    - The rest stays only two years in a row in the panel: firms interrogated in N-1 and N-2 are excluded, those interrogated in N-1 are kept, and some newly selected firms are drawn.

Main changes in the survey methodology

- 1992: reform leading to broadly the survey as it exists today. Most variables exist since 1992 or 1993.
- 2000: Increase of the threshold separating the simplified from the general questionnaire, from 5 million francs to 10 million francs. Some variables therefore are missing for firms that filed the simplified questionnaire in 2000.
- 2001: New firms are all interrogated in the first year. Until 2000, only 1 in 2 new firm was interrogated, the rest was kept for the following year.
- Change in units: in 1998, the answer is in francs and not in thousands francs anymore, because many errors were seen. In 2004, the answer is in thousands euros and not in euros anymore. After 2008, the answer is again asked in euros.

Some firms provide a "group" answer. Indeed for larger firms, R&D activity is more often organized at the group level than at the legal unit level. A variable lists the legal units concerned, but only after 2009.

B.6.2 The variables

- Total R&D Budget : total spending of a firm on R&D activities. It is the sum of internal and external spending. One has to be careful, this variable can count twice contracts made between two firms of the same group, once in internal spending and a second time in external spending.
- *of which* Current spending : gross wages of R&D workers and general expenses (spending in capital excluded), such as small tools, raw materials, administrative costs ...

- *of which* Gross wages of R&D workers. It includes all fiscal and social contributions.
- R&D workers : Researchers and technicians (support). in full time equivalent (prorata of time spent in R&D activities, with a minimum of 10%).
- *among which* Nb of researchers : scientists and engineers working at creating knowedge, products, processes, methods or new systems. It includes PhDs paid by the firm or high-level staff responsible with animating the researchers' teams. In full time equivalent.

C Additional Empirical Results

Table B1 presents regression results of an OLS estimation of equation 6 replacing the innovation left-hand-side with (the log of) total firm exports and dropping the export intensity from the demand shock computation. We thus use the following unadjusted export demand variables (at both the product M_s and industry M_I level):

$$\tilde{D}_{ft}^{M_s} = \sum_{j,s} \frac{X_{fjst_0}}{X_{ft_0}} \log M_{jst}$$
$$\tilde{D}_{ft}^{M_I} = \sum_{j,I} \frac{X_{fjIt_0}}{X_{ft_0}} \log M_{jIt}.$$

We see that those unadjusted export demand variables very strongly predict a firm's export response (first two columns). On the other hand, there is no evidence for a skewness effect for that export response – according to a firm's proximity to frontier. Our theoretical model predicts that the skewness effect evolves slowly over time as competition increases. The innovation response is forward looking and captures this anticipated effect, whereas the export measure does not.

Table B1: Impact of the Demand shock on firm's exports

Dependent variable	log(Exports)	log(Exports)	log(Exports)	log(Exports)
Demand Shock	$\tilde{D}_f^{M_s}$	$\tilde{D}_f^{M_I}$	$\tilde{D}_f^{M_s}$	$\tilde{D}_f^{M_I}$
	(1)	(2)	(3)	(4)
Demand	0.0419***	0.0592***	0.0334	0.0537**
	(0.0135)	(0.0164)	(0.0228)	(0.0260)
Decile × demand			0.00203	0.00135
			(0.00396)	(0.00453)
Nb of observation	72,380	72,416	72,380	72,416
R^2	0.855	0.856	0.855	0.856

Notes: Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute an the export demand shocks $\tilde{D}_{ft}^{M_s}$ and $\tilde{D}_{ft}^{M_I}$. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B2 considers more aggregated (across industries and products) demand shock measure using the GDP of destination j at t instead of world imports (excluding France) for a particular industry or product. Namely:

$$D^G_{ft} = \frac{X^*_{ft_0}}{S^*_{ft_0}} \sum_j \frac{X_{jt_0}}{X_{ft_0}} \log GDP_{jt}.$$

Table B2: Other demand shock

Dependent variable	All patents	Triadic patents	EPO patents
Demand measure	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$
	(1)	(2)	(3)
Demand	-3.037**	-0.217*	-0.448**
	(1.466)	(0.119)	(0.195)
Decile × Demand	0.852**	0.103***	0.149***
	(0.394)	(0.0328)	(0.0544)
Nb of observations	77,002	77,002	77,002
R^2	0.891	0.753	0.838

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute an export demand shock D^G_{ft}. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B3: Different trimming

Dependent variable	All patents					
Demand Measure	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$	$D^{M_s}_{ft}$
Trimming	2.5% (baseline)	0%	1%	2%	3%	5%
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-3.260***	-0.751**	-1.994***	-3.052***	-3.491***	-3.474***
	(1.014)	(0.305)	(0.745)	(0.925)	(1.119)	(1.256)
Decile × Demand	0.960***	0.166**	0.510***	0.842***	1.065***	1.086***
	(0.255)	(0.0816)	(0.169)	(0.227)	(0.285)	(0.327)
Nb of observation	77,901	82,043	80,378	78,722	77,077	73,784
R^2	0.897	0.881	0.892	0.896	0.898	0.908

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Different trimming on extreme variations of the Demand variable are done. Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.significance.

Table B4: Removing first years

Dependent variable	All patents		Triadic patents		EPO patents	
Demand Measure	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$
Years removed	$t < t_0 + 2$	$t < t_0 + 3$	$t < t_0 + 2$	$t < t_0 + 3$	$t < t_0 + 2$	$t < t_0 + 3$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-2.703***	-2.378**	-0.233***	-0.203***	-0.339***	-0.321**
	(1.003)	(0.938)	(0.0788)	(0.0733)	(0.129)	(0.129)
Decile × Demand	0.811***	0.654***	0.0752***	0.0620***	0.112***	0.0896***
	(0.249)	(0.229)	(0.0194)	(0.0172)	(0.0298)	(0.0292)
Nb of observation	72,265	66,684	72,265	66,684	72,265	66,684
R^2	0.911	0.920	0.763	0.763	0.870	0.885

Notes: This table presents regression results of an OLS estimation of equation 6. First years following t_0 are excluded from the estimation. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B5: Baseline results - Clustered standard errors

Dependent variable	All patents		Triadic patents		EPO patents	
Demand measure	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-3.260**	-2.578*	-0.265**	-0.224**	-0.368**	-0.447**
	(1.475)	(1.530)	(0.115)	(0.112)	(0.168)	(0.200)
Decile × Demand	0.960***	0.909**	0.0859***	0.0862***	0.125***	0.114**
	(0.372)	(0.444)	(0.0287)	(0.0327)	(0.0397)	(0.0554)
Nb of observation	77,901	77,918	77,901	77,918	77,901	77,918
R^2	0.897	0.888	0.759	0.747	0.849	0.836

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Heteroskedasticity robust standard errors clustered at the firm level ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B6: Poisson regressions

Dependent variable	All patents	Triadic patents	EPO patents
Demand measure	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$	$D_{ft}^{M_s}$
	(1)	(2)	(3)
Demand	-0.652***	-0.937***	-0.466*
	(0.208)	(0.360)	(0.246)
Decile × Demand	0.127***	0.164***	0.103***
	(0.0292)	(0.0481)	(0.0336)
Nb of observations	73,488	18,410	47,648

Notes: This table presents regression results of a Poisson estimation of equation 7. To obtain integer dependent variables, we do not use the fractional count (using these integer number with OLS has negligible effects) . Coefficients and standard errors are obtained using a maximum likelihood estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B7: Excluding leaders

Dependent variable	All patents		Triadic patents		EPO patents	
Demand measure	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$	$D_{ft}^{M_s}$	$D_{ft}^{M_I}$
	(1)	(2)	(3)	(4)	(5)	(6)
Demand	-2.820***	-2.730**	-0.251***	-0.219***	-0.357***	-0.482***
	(0.970)	(1.074)	(0.0838)	(0.0849)	(0.122)	(0.145)
interac	0.766***	1.246***	0.0790***	0.104***	0.122***	0.181***
	(0.239)	(0.318)	(0.0199)	(0.0244)	(0.0296)	(0.0405)
Nb of observation	77790	77806	77790	77806	77790	77806
R^2	0.897	0.887	0.751	0.748	0.846	0.835

Notes: This table presents regression results of an OLS estimation of equation 6. Sample includes manufacturing firms with at least one patent in 1995-2012 and for which we can compute the export demand shock (see section 4.1). The Demand variable does not include country j and products s for a firm f with a market share above 10% for the pair (j, s). Coefficients and standard errors are obtained using a panel fixed-effect estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator with a bandwidth set to 5 years. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

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"SCAN" (Supply Chain Alert Notification) monitoring system

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“SCAN” (Supply Chain Alert Notification) monitoring system[1]

Abstract

This note proposes an indicator-based mechanism in order to monitor the evolution of supply chains in the European Union (EU) and identify potential distress. Current events, such as COVID-19 or the Russian aggression against Ukraine, have highlighted the need for a better risk assessment of supply chains, particularly in strategic areas, with the ultimate goal of detecting disruptions as early as possible to avoid potential adverse effects on the economy and society. The proposed monitoring system is entitled “SCAN” (Supply Chain Alert Notification) and its main goal is to identify significant inflationary pressures and/or shortages, resulting from imbalances between demand and supply. This data-driven system could alert policy makers on possible supply chain disruptions, which can occur for specific products and sectors. The SCAN is first applied at the product level, where supply chain disruptions start to materialise. In order to be able to have targeted conclusions, we illustrate how this mechanism performs by focusing on a set of important commodities in two strategic settings – i.e. production of solar panels, commodities affected by the Russian invasion. The SCAN is then applied for the universe of sectors to capture signals of distress with more important aggregate consequences.

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1. Introduction

The EU benefits from world markets being open and integrated in global value chains both in terms of efficiency and resilience, through cost reduction, economies of scale, increase in innovation, risk reduction or access to foreign inputs (see for instance Shu and Steinwender, 2019; Akcigit and Melitz, 2021; Baldwin and Freeman, 2021). However, despite the overall efficiency and resilience considerations, disruptions in global value chains can affect specific products and inputs that are particularly critical for consumers and producers, leading to important market failures. Indeed, recent events, such as the COVID-19 pandemic and the Russian aggression against Ukraine, triggered several supply chains disruptions that have led to price increases and/or shortages for a wide range of products. Given the increasing economic relevance of these types of disruptions, monitoring the situation of EU supply chains is key to increase preparedness by supporting evidence-based policy making.

The development of tools aiming at monitoring supply chains is not a new concept, as this allows both companies and policy makers to increase preparedness in times of crises. For instance, some companies use developed risk monitoring technologies, targeted to the scope of their business, to understand which disruptions are likely to arise in their specific supply chains and how to best respond to these disruptions.[2] However, the idea of developing tools to monitor supply chains extends well beyond individual businesses. The public sector, the international bodies and the research circles are also making active efforts in this area, in order to get a better grasp of the situation and ensure a smooth functioning of the economy. For example, when it comes to certain agricultural goods, an inter-agency platform – the Agricultural Market Information System (AMIS) – was introduced in 2011 to enhance food market transparency and policy responses for food security.[3] AMIS analyses global food supplies for wheat, maize, rice and soybeans, while providing a platform to coordinate policy responses in times of crises. Another example could be the World Bank's efforts to monitor the commodity markets in terms of prices and produce economic forecasts.[4] Nevertheless, despite these public efforts, the existing monitoring tools in the EU are rather scarce or targeted to specific products. Most importantly, the majority of these cases do not allow the tracking of the real-time evolution of supply chains.[5]

We contribute by proposing a monitoring system, entitled "SCAN" (Supply Chain Alert Notification), targeted to identify signs of distress in EU's supply chains.[6] More precisely, our monitoring system is intended to capture potential significant inflationary pressures and/or shortages, which can result from imbalances between demand and supply, where supply cannot keep up with demand. More precisely, the issue can be due to a demand increase for a constant supply (e.g. increase in the consumer demand of surgical masks), a supply decrease for a constant demand (e.g. logistic crunches due to pandemic restrictions) or a demand increase combined with a supply decrease (e.g. the case of wood where the renovation wave led to a demand increase, but there were also some identified supply

[2] For example, the *Gartner Supply Chain Top 25* identifies characteristics of firms that demonstrate excellence in supply chain management aiming at building resilience. See for instance the "Gartner Supply Chain Top 25" for specific examples of global firms that according to their methodology are performing exceptionally well.

[3] https://app.amis-outlook.org/#/market-database/supply-and-demand-overview

[4] https://www.worldbank.org/en/research/commodity-markets#1

[5] The data are usually annual and focus on monitoring specific commodities, without taking into account the supply chains of those commodities.

[6] This monitoring tool can be applied to other countries subject to data availability. Having results from different countries across the world would improve the overall assessment of supply chain distress.

problems). The SCAN tool is defined at two levels of aggregation: 1) products, with a focus on strategic ones (either linked to specific contexts such as the Russian invasion of Ukraine or used as inputs to produce strategic products), and 2) industrial sectors, with a comprehensive coverage. The two levels of monitoring serve different purposes. First, since analysing the supply chain of the universe of products would not allow for a targeted monitoring due to the high number of products (more than 5,000 depending on the product aggregation), the SCAN at the product level allows to focus on strategic and/or critical products. While anticipating disruptions of specific products through the use of quantitative indicators is outside the scope of this paper, we can narrow down our monitoring to strategic products where disruptions are expected to occur. For example, as a consequence of the Russian invasion of Ukraine, economic rationale suggests that distress might occur in those products where the EU is heavily dependent on Russia, considering that not immediate alternatives are found. In addition, the green transition is increasing the demand for strategic inputs, potentially generating supply chain distress. In parallel, we analyse the supply chains of the universe of industrial sectors as it allows to identify disruptions with more important consequences at the aggregate level.

Our aim is to identify indicators with the same rationale at different levels of aggregation. To this end, we rely primarily on a set of core indicators – summarised under the SCAN – hinting to potential significant inflationary pressures and/or shortages both at product and sectoral levels. These metrics are then complemented with other indicators, which give additional information on the level of distress, but which are specific to each level of aggregation. While these tools do not provide a comprehensive assessment of the situation of supply chains, they can provide warnings that the ex-ante potential distress product/sector is materialising.

2. Monitoring at a product level

Supply chain distress starts by materialising in specific products, as it was the case for surgical masks and semiconductors during the COVID-19 pandemic, as well as for various commodities in the context of the Russian aggression against Ukraine. While a general monitoring system at the product level can be very informative, exploring systematically the universe (above 5,000 products depending on the level of aggregation) of products will not necessarily bring much value added due to the high number of products. Indeed, the focus on specific baskets of products experiencing potential distress can lead to more targeted conclusions. In what follows, we focus on products relevant in specific contexts - such as the Russian invasion of Ukraine - or further used in the production of strategic products, such as green technologies. On the latter, we rely on the example of raw materials that are used in the production of solar panels, as this can provide early warnings regarding bottlenecks that can impede ramping up the production of this particular renewable technology.

Two types of indicators are used to identify supply chain disruptions at the product level:

- **(Block 1) High-frequency indicators to capture price increases and/or shortages:** This set of indicators use high-frequency proxies of imported prices and quantities in the EU computed at a very disaggregated product level based on customs data.[7] The most distressed products are those that experience a significant

[7] These indicators can be updated every two weeks.

import price increase combined with a significant decrease in imported quantities.[8] [9] High-frequency customs data are also used to detect abnormal falls in the quantity imported, hinting to a potential shortage. More precisely, for both import prices and quantities, we compare the average of the last available three months with the average of the same period over the previous three years.[10] The comparison with the average of the previous three years is used to smooth out the potential abnormalities specific to a given year. All in all, the evolution of both import prices and quantities can be reported every two weeks to prevent some false alarms given the high volatility of trade flows in some products.

- **(Block 2) Structural indicators to assess the ex-ante risk of disruptions:** Block 2 relies on more structural indicators associated with an important ex-ante risk that, under particular circumstances, can materialize in significant import price and quantity fluctuations.[11] In addition, if this risk materialises, these indicators will identify products where the EU is heavily dependent on third markets and more likely to face to supply chains disruptions.[12] To measure the level of foreign dependency of a product, we monitor the concentration of extra-EU imports, as well as the substitution potential of these extra-EU imports with the EU domestic production. The economic intuition behind these indicators considered together is that if the EU relies on heavily concentrated imports without having the domestic production capacity, all else equal, bottlenecks in supply chains due to external shocks can materialise in price increases and/or shortages.

  For concentration, we use two complementary indicators: (1) the extra-EU import concentration and (2) the share of the first source in extra-EU imports, both computed based on the COMEXT dataset. Products highlighted as facing a high ex-ante risk include those with an HHI index above 0.4 (i.e. average imports originating in less than 3 countries) and the share of the first source above 50%.[13] For the substitutability of extra-EU imports with EU's domestic production, we also use two complementary indicators: (1) the ratio between extra-EU imports and total EU exports (proxy for production) computed based on the COMEXT dataset and (2) the exposure index defined as the share of extra-EU imports in EU total supply (sum of domestic production and extra-EU imports), where the trade data from COMEXT is complemented with production information (PRODCOM). The chosen thresholds indicating a high ex-ante risk for the first and second indicator are 1 and 0.6,

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[8] Many factors can be associated with price increases and/or shortages at the product level, including trade policy interventions, exchange rate evolutions, shipping bottlenecks, among many others. Given that the effect of these factors across products is heterogeneous, the available data at hand do not allow to dig into all the factors driving the observed disruptions at the product level. Therefore, once disruptions are identified for specific products, our methodology should be complemented with deeper analyses and expert knowledge, in order to have a better understanding of the causes behind the observed distress.

[9] Future potential venues of analysis include calculating alternative proxing of price variations. This could include alternative indicators from trade statististics, as well as alternative sources such as listed price statistics.

[10] For example, if the latest available information is May 2022, the monitoring will take into account the average of the months of May, April and March for 2022 compared to the average of the same three months in 2021, 2020 and 2019.

[11] For more details for the underlying mechanisms, see the first issue of the Directorate-General for Internal Market's Single Market Economic Papers series on *Detecting and Analysing Supply Chain Disruptions.*

[12] For instance, the production of magnesium is heavily concentrated, with China controlling 89% of the world production. The energy crisis in China, including coal shortages, combined with the attempt to reach lower emission targets led to the abrupt closure of some plants producing magnesium. This has induced important disruptions for the EU's supply chains heavily reliant on magnesium.

[13] SWD (2021) 352 on strategic dependencies and capacities: swd-strategic-dependencies-capacities_en.pdf (europa.eu).

respectively.[14] In line with previous European Commission documents,[15] these thresholds suggest that, all else equal, the risk of disruption is considered to be higher for those products where domestic production cannot replace foreign imports. Indeed, the threshold equal to 1 indicates that EU imports are higher than EU exports, which means that in the case of crisis, existing export capacity cannot compensate potentially affected imports.[16] In the case of the threshold equals to 0.6, it considers products where imports accounts for more than 60% of total domestic supply (domestic production plus EU imports). Those products that have values above the indicated thresholds in all four structural indicators present a high risk of disruptions and those products with values above the indicated thresholds in a sub-block of two complementary indicators are considered as medium risk.

2.1 The example of raw materials relevant in the context of the Russian invasion of Ukraine

To illustrate the SCAN at the product level, we focus on a selected basket of raw materials that are known to be particularly relevant in the context of the Russian invasion of Ukraine. The two blocks of indicators described above are displayed in the form of a product SCAN containing a scoreboard and a graph, which show potential problematic products facing supply chain distress. Once again, the information provided in this tool should be complemented with an in-depth analysis, in order to validate and understand the factors behind the observed trends.

Table 1 presents the indicators used to analyse distress in the form of a scoreboard. It focuses on the list of commodities most affected by the Russian invasion of Ukraine. Thus, it includes indicators about the importance of Russia in EU's imports (Columns 1 and 2). Columns 3 and 4 present the high-frequency indicators included in Block 1. The following four columns include the foreign dependency structural indicators from Block 2. Finally, in Column 9, those products with a high ex-ante risk of disruptions are highlighted with two asterisk (**) and those with a medium risk are highlighted with one asterisk (*).

Graph 1 displays the evolution of import prices and quantities for all selected commodities as highlighted in Columns 3 and 4 of Table 1. Two shaded areas aim at identifying the most problematic products that seem to be relatively more affected by ongoing supply chain distress. In this respect, two cases can be distinguished. The first case, corresponding to quadrant II, shows products experiencing an increase in import price combined with a decrease in quantities imported and corresponds to our definition of potential disruptions. The second case, corresponding to quadrant I and products above the 45 degree line, shows commodities that are experiencing a stronger important increase in import price compared to the increase in quantities imported, which might potentially induce disruptions. The intensity of distress of a product can be measured by the distance to the "north-west" corner of quadrant II, where the closer the product is to this upper corner, the higher its potential distress (represented by the darker colour). In the graph, we also highlight with two asterisk

[14] Note that both indicators have their own limitations and for this reason are complementary. While the ratio between extra-EU imports and total EU exports does not capture total domestic production, the share of extra-EU imports and EU total supply replies on two separate databases (COMEXT and PRODCOM), which can lead to some aggregation concerns.

[15] SWD(2021) 352 final on EU strategic dependencies and capacities

[16] Indeed, Benoît et al. (2022) show that products that experience important import price increases and quantity decreases during 2021 (the first stages of the Covid-19 pandemic) are those that have a level of concentration above the chosen thresholds and where the EU is highly reliant on foreign imports.

(**) those products with a high ex-ante risk of disruptions and with one asterisk (*) those characterised by a medium ex-ante risk.

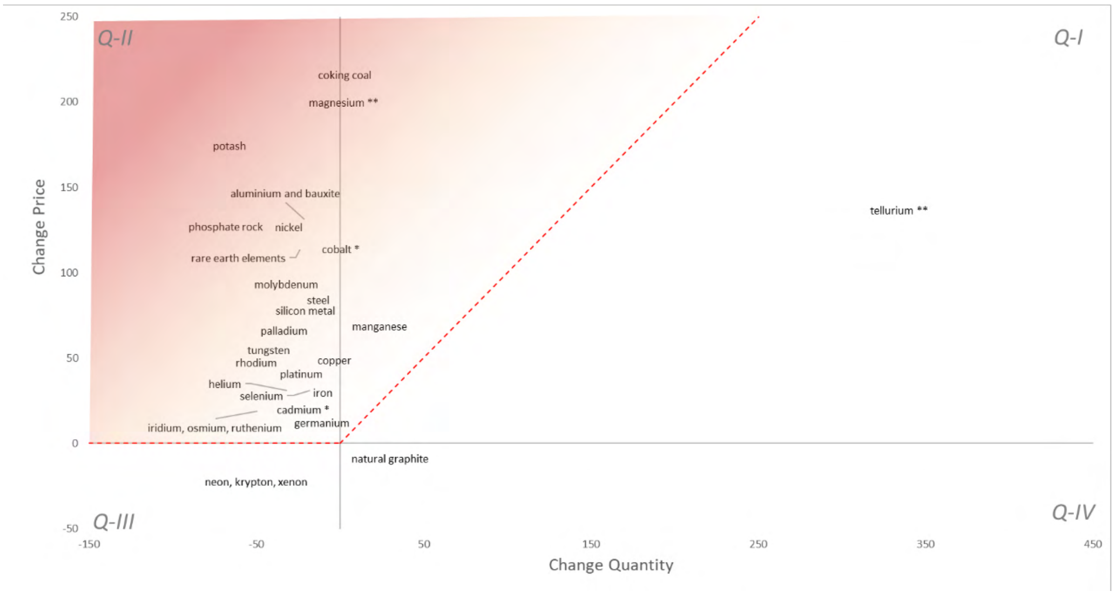
Table 1: Illustration of the SCAN at a product level

	Russia's importance in extra-EU imports		Block 1: High-frequency indicators		Block 2: Structural Indicators				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RU share of EU imports	RU rank as source of import	Change in import price	Change in quantity	Concentration of extra-EU imports	Share 1st source in extra-EU imports	Ratio of extra-EU imports and total EU exports	Exposure index (without Exports)	Important ex ante risk of disruptions
aluminium and bauxite	7.1%	3	131%	-21%	0.1	27.10%	1	46.94%	
cadmium	13.8%	2	20%	-22%	0.7	83.90%	1	0.27%	*
coking coal	11.6%	3	209%	3%	0.3	41.90%	1.2		
copper	36.6%	1	49%	-3%	0.2	36.60%	0.6	32.44%	
germanium	0.2%	9	12%	-10%	0.3	50.60%	1.6	53.94%	
helium	1.0%	6	31%	-32%	0.3	41.70%	0.6	63.00%	
iridium, osmium, ruthenium	8.6%	4	19%	-49%	0.3	46.90%	0.3	42.99%	
iron	12.7%	5	30%	-18%	0.2	23.80%	2.1	79.50%	
magnesium	1.1%	4	200%	2%	0.8	91.30%	1.3	82.70%	**
manganese	1.2%	8	69%	24%	0.3	41.10%	1.4	67.16%	
molybdenum	1.9%	8	86%	-30%	0.2	22.20%	1	74.16%	
natural graphite	1.4%	11	-1%	4%	0.2	25.20%	1.7	3.91%	
neon, krypton, xenon	20.2%	3	-22%	-50%	0.2	33.60%	0.3	36.19%	
nickel	54.3%	1	130%	-35%	0.3	54.30%	1.2	74.31%	
palladium	37.4%	1	66%	-34%	0.3	37.40%	0.8	84.11%	
phosphate rock	40.7%	1	127%	-42%	0.3	40.70%	11.3	95.62%	
platinum	10.5%	4	32%	-12%	0.3	46.30%	0.6	64.36%	
potash	23.3%	3	174%	-66%	0.2	31.80%	2.7	31.56%	
rare earth elements	0.9%	8	114%	-24%	0.2	34.70%	0.9	21.07%	
rhodium	15.3%	3	47%	-50%	0.3	49.30%	0.5	77.38%	
selenium	31.0%	1	31%	-18%	0.2	31.00%	0.4	54.18%	
silicon metal	1.0%	11	82%	-20%	0.3	50.00%	1	45.29%	
steel	44.8%	1	84%	-13%	0.3	44.80%	1.2	4.42%	
tellurium	1.4%	5	137%	334%	0.4	62.30%	3.1	65.66%	**
tungsten	6.6%	6	55%	-42%	0.2	23.70%	0.4	13.61%	

Source: GROW A1 calculations based on the European Commission customs database, COMEXT and PRODCOM.

Note: For indicators in Block 1, we rely on high-frequency customs data and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. For the first three indicators in Block 2 we use the most up-to-date information using trade data (COMEXT 2021) and for the fourth indicators, we use trade (COMEXT) and production (PRODCOM) for 2019, to avoid abnormal statistics resulting from the first year of the pandemic, as the most up-to-date data on production refer to 2020. Indicators in Block 2 allow to identify products with an important ex-ante risk of disruptions. Those products with a high risk are highlighted with two asterisk (**) and those with a medium risk are highlighted with one asterisk (*).

Graph 1: Identification of distressed products through the sectoral SCAN



Source: GROW A1 calculations based on the European Commission customs database, COMEXT and PRODCOM. Note: Reference period: Note: For indicators in Block 1, we rely on high-frequency customs data and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. Changes in import prices are captured by the Y axis and changes in imported quantities are captured by the X axis. This information is complemented with the indicators in Block 2, which allow to identify products with an important ex-ante risk of disruptions. Those products with a high risk are highlighted with two asterisks (**) and those with a medium risk are highlighted with one asterisk (*).

To sum up, almost all raw materials likely to be affected by the Russian aggression of Ukraine experience distress (i.e. import price increases and/or import quantity decreases). The few exceptions include tellurium, neon and natural graphite. Moreover, with the exception of tellurium, all raw materials with an important ex-ante risk of disruptions are subject to import price increases and import quantity decreases (i.e. magnesium, cobalt, cadmium).

2.2 The example of Solar Panels

To further illustrate the SCAN monitoring tool at the product level, we focus on a specific basket of products necessary to produce a strategic final good. Our pilot example uses the most upstream inputs (i.e. raw materials) used in the production of solar panels. Distress occurring in the most upstream part of the supply chain of solar panels can have important implications for ramping up the production of this renewable energy technology. The choice to focus on solar panels is motivated by various factors. First, solar photovoltaic (solar PV) technologies have become the world’s fastest-growing energy technology and play an important role in securing sufficient amounts of decarbonised electricity to meet the goals of the European Green Deal. Second, contrary to the wind sector where the EU industry has a strong position, the EU solar PV industry is more reliant on international supply and value chains. While the EU ranks high in terms of deployment of solar PV installations, EU companies only represent a very small part of global production. Finally, solar cells and panels are an example of a “common dependency”, where the EU and other global actors strongly depend on China’s (upstream) manufacturing capacities.

In order to identify the relevant raw materials used in the production of solar panels, we rely on the concept of technological designs, as different designs require different raw materials. Therefore, the main objective is to identify the prevailing technological designs in the market and trace the raw materials necessary to produce solar panels based on these designs.[17] To illustrate this product-level example, we start by identifying the prevailing technologies to produce solar panels and the raw materials used in their production. Then we follow the same steps/blocks as before.

The sequence of steps is presented below:

1. **Finding critical materials for the prevailing technological designs**

2. **Monitor the real-time evolution of import prices and quantities for each material** (Block 1)

3. **Monitor the systemic risk stemming from foreign dependencies for each material** (Block 2)

4. **Summarising the information using the previously discussed SCAN format – scoreboard and graph**

The first step of this methodology consists in identifying the raw materials used in the prevailing technology-designs of solar panels. Some of the most known designs are crystalline silicon based designs, cadmium telluride designs or cooper indium gallium diselenide designs.[18] A recent study from the Joint Research Centre (JRC) already puts forward the 17 most important raw-materials required to build solar panels.[19] Illustration 1 considers all materials used to manufacture any of these solar panels designs and highlights which of these materials can be considered as critical.[20] However, following the above-mentioned methodology, we focus our analysis only on the most relevant Solar Panels designs. As silicon wafers designs make up around 95% of the current market in Europe,[21] we focus our analysis on the materials used in these designs: Silica, Gallium, Boron, Phosphorus, Indium. To complement this analysis, we consider also four more materials that are always necessary to manufacture any kind of solar panel: Tin, Lead, Silver, Molybdenum. It is worth noting that Tin and Lead are substitutes, that is, they serve the same purpose in solar panels manufacturing.[22] As shown in Illustration 1 by the shaded areas, the final short-list of materials to include in our early warning mechanism for solar panels supply chains includes: Silica, Gallium, Boron, Phosphorus, Tin, Lead, Silver, Molybdenum. In this way, we

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[17] When looking at these technological designs, it is important to consider that some might be more prevailing in a market than others and their level of performance might vary, depending on their application. In terms of substitutability, there are two main considerations to be made (1) either the designs can substitute each other as they achieve similar and acceptable levels of performance (baking different cakes using different recipes), or (2) specific materials in each design can substitute each other as they are required for the same purpose (baking one cake using one recipe but changing one ingredient). When focusing on the prevailing technology designs to produce solar panels, these two aspects will be taken into consideration.

[18] Carrara, S., Alves Dias, P., Plazzotta, B. and Pavel, C. (2020). Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system, EUR 30095 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-76-16225-4 (online), doi:10.2760/160859 (online), JRC119941

[19] Joint Research Centre, Critical Raw Materials for Strategic Technologies and Sectors in the EU: A Foresight Study; ISBN 978-92-76-15336-8.

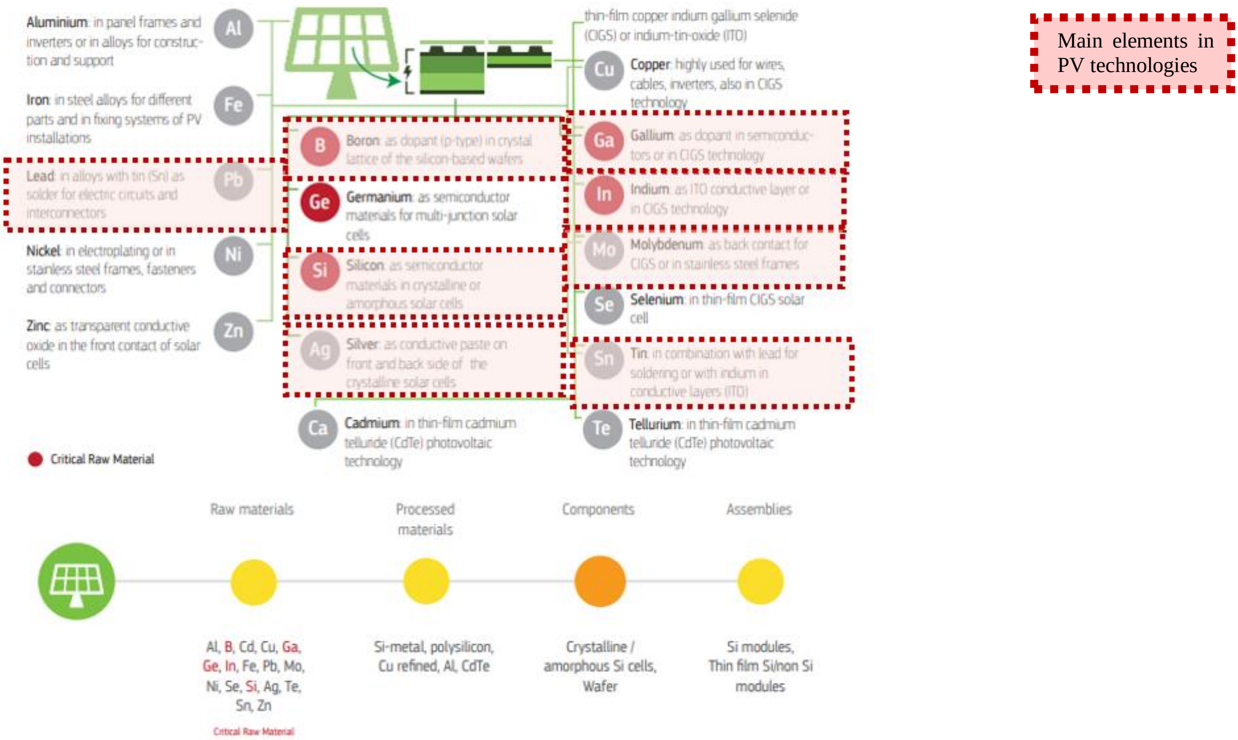
[20] COM(2020) 474 final; Critical Raw Materials Resilience: Charting a Path towards greater Security and Sustainability.

[21] Fraunhofer Institute for Solar Energy Systems, Photovoltaics report, 24 February 2022

[22] University of Oxford, Lead out, Tin in for a cheap solar cell, May 1st 2014

focus our analysis on only eight out of the initial 17 raw materials that make up solar panels. After identifying the relevant raw materials for the prevailing designs of solar panel technologies, we identify the relevant product codes in the trade and production data (see Annex for a detailed explanation).

Illustration 1 – Raw Materials used in PV technologies



Source: "European Commission, Critical materials for strategic technologies and sectors in the EU - a foresight study, 2020"

In the second step, we turn to Block 1, where high-frequency customs data on import prices and quantities are used for monitoring (i.e. dynamic monitoring). The third step focuses on Block 2, where in line with the previously established criteria, categories are used to highlight those products with an important ex-ante risk of disruptions. While this approach, based on hard data, is informative, it should be complemented with deeper analyses and expert assessment on each of these raw materials (e.g. Is the market of a specific material expected to increase in the next decades?). Finally, in the last step, two outputs are presented in the form of a scoreboard and a graph, which visually show the potentially problematic raw materials necessary for the production of solar panels.

Table 2 represents the scoreboard for the relevant raw materials for solar panels. Columns 1 and 2 present the high frequency indicators included in Block 1. The next four columns include the foreign dependency structural indicators from Block 2. Finally, in Column 7, the products with a high ex-ante risk of disruptions are highlighted with two asterisks (**) (i.e. phosphorus) and those with a medium ex-ante risk of disruptions are highlighted with one asterisk (*) (i.e. boron, gallium).

Graph 2 displays the evolution of import prices and quantities for all chosen raw materials captures in Block 1 in Table 2. As in the previous case, two shaded areas aim at identifying the raw materials that could be relatively more affected by supply chain distress as they are subject to inflationary and production pressures. In this respect, two cases can be distinguished. The first case, corresponding to quadrant II, shows raw materials experiencing an increase in import price combined with a decrease in quantities imported. The second case, corresponding to quadrant I and above the 45 degree line, shows raw materials which experience a more important increase in import price compared to the increase in quantities imported. Moreover, the intensity of distress of a raw material can be measured by the distance to the “north-west” corner of quadrant II, where the closer the product is to this upper corner, the higher its potential distress. In the shaded areas, the darker the colour, the more distressed a product is. Furthermore, we highlight with two asterisk (**) those products with a high ex-ante risk of disruptions (i.e. phosphorus) and with one asterisk (*) those characterised by a medium ex-ante risk (i.e. boron).

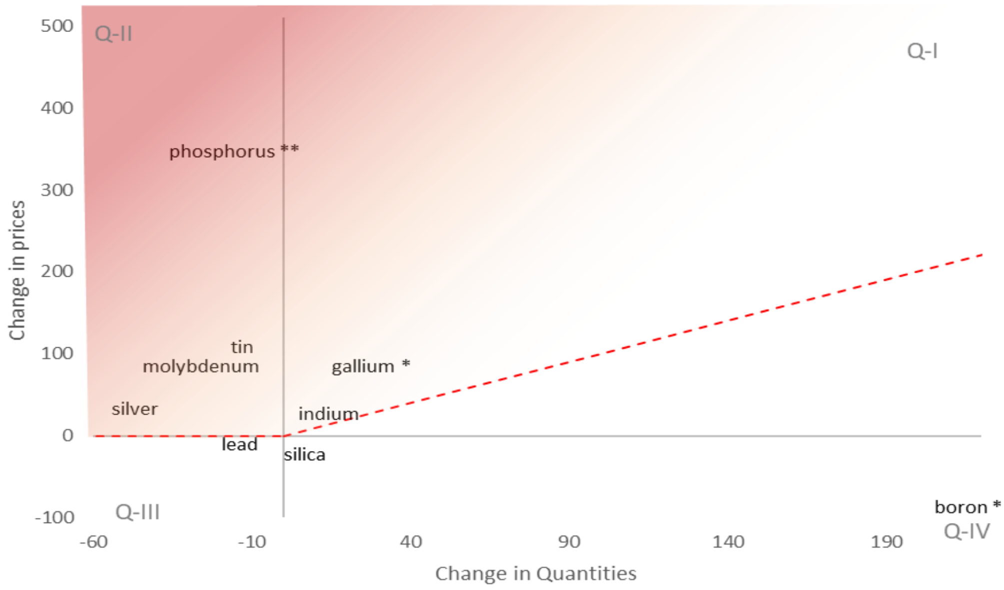
Table 2: Scoreboard for early warning monitoring of solar panels supply chains using critical raw materials

	Block 1: High-frequency indicators		Block 2: Structural Indicators				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Change in import price	Change in quantity	Concentration of extra-EU imports	Share 1st source in extra-EU imports	Ratio of extra-EU imports and total EU exports	Exposure index (without Exports)	Important ex ante risk of disruptions
boron	-86%	216%	0.7	83.10%	0.6	62.60%	*
gallium	85%	28%	0.7	85.50%	1.7	39.20%	*
indium	27%	15%	0.5	70.00%	0.5	36.50%	
lead	0%	-9%	0.1	21.60%	0.6	29.40%	
molybdenum	86%	-26%	0.2	26.20%	0.8	78.30%	
phosphorus	348%	-16%	0.4	59.60%	19	88.60%	**
silica	-22%	7%	0.3	41.10%	0.3	6.00%	
silver	33%	-47%	0.1	25.50%	1.5	12.20%	
tin	109%	-13%	0.2	39.50%	1	73.80%	

Source: GROW A1 calculations based on the European Commission customs database, COMEXT and PRODCOM.

Note: For indicators in Block 1, we rely on high-frequency customs data and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. For the first indicators in Block 2 we use the most up-to-date information using trade data (COMEXT 2021) and for the fourth indicators, we use trade (COMEXT) and production (PRODCOM) for 2019, to avoid abnormal statistics resulting from the first year of the pandemic. Indicators in Block 2 allow to identify products with an important ex-ante risk of disruptions. Those products with a high risk are highlighted with two asterisk (**) and those with a medium risk are highlighted with one asterisk (*).

Graph 2: Mapping of solar panels raw materials in terms of their price, quantity, and level of exposure and dependency from extra-EU sources.



Source: GROW A1 calculations based on the European Commission customs database, COMEXT and PRODCOM. Note: Reference period: Note: For indicators in Block 1, we rely on high-frequency customs data and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. Changes in import prices are captured by the Y axis and changes in imported quantities are captured by the X axis. This information is complemented with the indicators in Block 2, which allow to identify products with an important ex-ante risk of disruptions. Those products with a high risk are highlighted with two asterisk (**) and those with a medium risk are highlighted with one asterisk (*).

The methodology proposed for the product-level SCAN proposes a systematic way to monitor products' supply chains by focusing on the raw materials that make up the most prevailing technological designs. For the case of solar panels, there is only one most prevailing design, crystalline silicon design, so that is where we focused our analysis. However, using the SCAN on other products might mean that more than one technological design's raw materials would be tracked. All in all, when it comes to the monitoring of raw materials used in the prevailing technological designs for solar panels, it appears that, with the exceptions of lead, silica and boron, all raw materials experience distress (i.e. import price increases and/or import quantity decreases). For instance, phosphorus, which is a product with a high ex-ante underlying risk, is the raw material with the highest import price increase, combined with an import quantity decrease.

3. Monitoring at a sectoral level

The product monitoring system is then augmented with a SCAN monitoring system at a sectoral level.[23] Similarly to our product analysis, the sectoral monitoring system is intended to capture aggregate significant inflationary pressures and/or shortages. These variables are then complemented with relevant information, which is only available at this level of aggregation. In particular, we refer to quarterly firm level survey data related to self-reported constraints, which give another level of insights on the level of distress across industrial sectors. The advantage of this level of aggregation is that it allows to identify distress with an economically significant aggregate effect for the EU.[24] These indicators are then grouped in two blocks:

- **(Block 1) High-frequency indicators to capture price increases and/or shortages:** Block 1 uses monthly indicators on the evolution of sectoral prices and production. In order to identify distressed sectors in terms of inflationary pressures and/or shortages, two main variables are used in Block 1, namely production and producer prices. As in products, the most distressed sectors are those that experience a significant price increase combined with a significant decrease in quantities produced. For this reason, we compare the average of production and producer prices for the last three months available with their average over the same period in 2021, 2020, and 2019. Comparing the average indicator in the period 2022 with the previous three years prevents our results from being influenced by sectoral specificities over a specific year (for instance, during the COVID-19 pandemic). In addition, the information on producer prices is also complemented with information on import prices (used in the product analysis) in order to understand whether the sectoral inflation is imported. However, looking at the two price series, we observe that they seem to be very correlated. Therefore, the interpretation of the results will mainly focus on producer prices. The data on these aspects, which are extracted from the Short-Term Business Statistics, are available on a monthly basis and have a reporting delay of approximately 2-3 months.

- **(Block 2) Indicators on the type of constraints faced by firms in various sectors:** Survey data are only available at this level of aggregation. The indicators grouped in Block 2 refer to the main self-reported factors restraining the production of firms in the EU: labour, equipment and inputs, finance and other. In terms of monitoring supply chains, the question related to constraints in “equipment and inputs” is, in principle, the most relevant category. The information is extracted from the Business and Consumer surveys,[25] which are regularly updated on a quarterly basis.

[23] The sectoral monitoring tool builds on the Shortages Alert Mechanism (SAM) presented in the first issue of the Directorate-General for Internal Market’s Single Market Economic Papers: “Detecting and Analysing Supply Chain Disruptions” (Benoit et al., 2022). It improves the SAM by considering additional indicators, namely production and import prices. Also, instead of focusing on values for all indicators at different moments as it was the case in the SAM, the SCAN displays directly the changes in the values of these indicators, so as to identify more easily problematic sectors. Finally, the most up-to-date information is used for showing how the SCAN is implemented.

[24] Subject to data availability, the analysis can in principle also be reproduced at the Member State level.

[25] DG ECFIN conducts regular harmonised surveys for different sectors of the economies in the EU and in the applicant countries. They are addressed to representatives of the industry (manufacturing), services, retail trade and construction sectors, as well as to consumers. These surveys allow comparisons among different countries' business cycles and have become an indispensable tool for monitoring the evolution of the EU and the euro area economies, as well as monitoring developments in the applicant countries.

Similarly to the analysis on products, the sectoral SCAN displays the different indicators in a visual manner in the form of a scoreboard and a graph. These tools are meant to aggregate all of the information mentioned above and visually show the potential problematic sectors facing inflationary pressures and/or shortages, as well as the sectors where firms are self-reporting important input constraints. Once again, the information provided in this tool should be complemented with an in-depth qualitative analysis in order to validate and understand the factors behind the observed evolutions.

Table 3 summarises the above information for industrial sectors. Columns 1, 2, and 3 present the indicators from Block 1, namely the evolution of production and producer prices, also complemented with the evolution of import prices for completeness. This information allows to identify distressed sectors in terms of inflationary pressures and/or shortages. The next four columns present the share of firms that indicated a particular production constraint (i.e. labour, equipment, other or finance) in the latest quarter when this information was collected. The sectors highlighted with an asterisk (*) are those in which firms signal their input shortages (i.e. measured as above the sectoral median).[26]

Graph 3 displays the evolution of production in comparison with producer prices for all industrial sectors as displayed in Column 1 and 3 of Table 3. Two shaded areas aim at identifying the sectors that could be relatively more affected by supply chain distress as they are subject to inflationary and production pressures. In this respect, two cases can be distinguished. The first case, corresponding to quadrant II, shows sectors experiencing an increase in import price combined with a decrease in quantities imported. The second case, corresponding to quadrant I and above the 45 degree line, shows sectors which experience a more important increase in import price compared to the increase in quantities imported. Moreover, the intensity of distress of a sector can be measured by the distance to the "north-west" corner of quadrant II, where the closer the product is to this upper corner, the higher its potential distress. In the shaded areas, the darker the colour, the more distressed a product is. The sectors highlighted with an asterisk (*) are those in which firms signal their input shortages (i.e. measured as above the sectoral median).

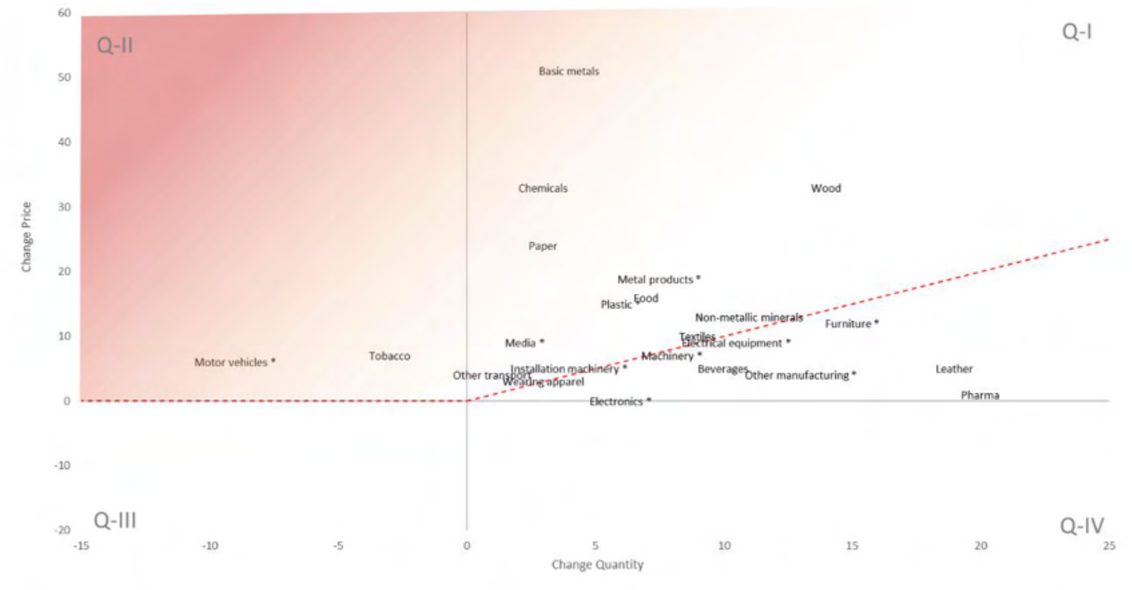
[26] The median is used to highlight in relative terms the most distressed sectors.

Table 3: Illustration of the sectoral SCAN

Nace rev 2		Last three month average (2022 compared to 2021, 2019, 2018)			Answers provided during Q1 2022				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Producer prices (sts_inpp_m)	Import prices (sts_inpi_m)	Production (sts_inpr_m)	Labour (% s.a.)	Shortage of material and/or equipment (% s.a.)	Other (% s.a.)	Financial (% s.a.)	Shortage of material and/or equipment (> median)
C10	**Food**	16%	15%	7%	27%	41%	18%	7%	
C11	**Beverages**	5%	3%	10%	15%	33%	16%	7%	
C12	**Tobacco**	7%	1%	-3%					
C13	**Textiles**	10%	10%	9%	22%	29%	26%	8%	
C14	**Wearing apparel**	3%	4%	3%	14%	26%	20%	9%	
C15	**Leather**	5%	5%	19%	19%	19%	16%	4%	
C16	**Wood**	33%	31%	14%	27%	41%	15%	7%	
C17	**Paper**	24%	20%	3%	21%	37%	18%	6%	
C18	**Media**	9%		2%	29%	55%	16%	8%	*
C19	**Petroleum**	81%	62%	3%	3%	33%	17%	1%	
C20	**Chemicals**	33%	32%	3%	13%	42%	12%	5%	
C21	**Pharma**	1%	6%	20%	24%	38%	8%	2%	
C22	**Plastic**	15%	11%	6%	33%	45%	19%	5%	*
C23	**Non-metallic minerals**	13%	9%	11%	25%	36%	25%	6%	
C24	**Basic metals**	51%	49%	4%	18%	33%	30%	8%	
C25	**Metal products**	17%	14%	7%	32%	48%	21%	7%	*
C26	**Electronics**	0%	2%	6%	29%	65%	17%	7%	*
C27	**Electrical equipment**	9%	9%	10%	27%	68%	13%	4%	*
C28	**Machinery**	7%	6%	8%	29%	66%	16%	3%	*
C29	**Motor vehicles**	6%	6%	-9%	22%	69%	14%	4%	*
C30	**Other transport**	4%	7%	1%	12%	42%	20%	2%	
C31	**Furniture**	12%	9%	15%	27%	44%	17%	8%	*
C32	**Other manufacturing**	4%	4%	13%	32%	46%	11%	4%	*
C33	**Installation machinery**	5%		4%	29%	56%	13%	6%	*

Source: GROW A1 calculations based on Short-Term business statistics (Eurostat) and Business and Consumer Surveys. Note: For indicators in Block 1, we rely on monthly short-term business statistics and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. For the data in Block 2, we use the most up-to-date information using Business and Consumer Surveys. Indicators in Block 2 allow to identify problematic sectors by identifying those sectors where firms are reporting particularly important production constraints. Sectors situated above the sectoral median in terms of number of firms reporting shortages of material and/or equipment are highlighted with an asterisk (*).

Graph 3: Identification of distressed sectors through the sectoral SCAN



Source: GROW A1 calculations based on Short-Term business statistics (Eurostat) and Business and Consumer Surveys. Note: For indicators in Block 1, we rely on monthly short-term business statistics and we compare the average for March/April/May 2022 with the average of the same period of 2021, 2020 and 2019. Changes in import prices are captured by the Y axis and changes in production are captured by the X-axis. This information is complemented with the indicators in Block 2, which allow to identify sectors where there is a particularly high self-reporting firm response in terms of constraints. For illustration purposes, sectors above the industrial median in self-reporting input constraints are highlighting with an asterisk (*).

4. Conclusion

In this note, we proposed a frequently updated quantitative monitoring tool to detect possible supply chains disruptions.[27] More precisely, the SCAN monitoring tool offers insights to policy makers on the potential supply chain disruptions at two levels of aggregation, namely products and sectors. The core indicators included in the SCAN can be updated twice per month for products (with a lag of two weeks) and monthly for sectors (with a lag of up to two or three months).

Given the high-frequency of the customs data, the SCAN monitoring tool allows to detect supply chain disruptions at the product level almost as soon as they materialise. While this data-driven exercise cannot forecast non-materialised disruptions, the use of structural indicators can give an indication on ex-ante vulnerabilities that can materialise in supply chain disruptions if specific events occur. In addition, the ongoing monitoring of the situation allows to infer whether the observed product disruptions are transitory or persistent. If the same types of disruptions occur in successive updates of the SCAN, this suggests that the problem is persistent and particular attention might be required on the identified issue.

[27] Some indicators can be updated twice a month (i.e. evolution of import prices and quantities at the product level), while other indicators could be updated monthly (i.e. evolution of producer prices and production at the sectoral level) or quarterly (i.e. production constraints faced by firms). While structural indicators do not vary significantly in the short-term, structural indicators can be updated on a yearly basis.

Moreover, based on the product-level SCAN, which is updated in almost real time, one can already predict the more aggregated sectoral implications of product-specific disruptions which might materialise at a later stage. Then, the sectoral SCAN allows to get a better understanding of the sectoral situation.

While the SCAN at the product level focused on the pilot example of solar panels, the same type of exercise can in principle be performed for other strategic products, including semiconductors and other green transition technologies such as heat-pumps, electrolysers or wind-technologies. Expanding the implementation of the SCAN monitoring tool to other products would provide additional insights as to which products are more vulnerable to supply chains disruptions so as to motivate policy intervention when justified.[28]

To sum up, the SCAN collects highly relevant indicators with the objective of monitoring supply chains disruptions in the EU. However, given the intrinsic international nature of the problem it aims to address, as well as the similarity of the challenges faced by other regions in the world, this methodology can be a starting point for discussions with other partners sharing similar objectives.

[28] In order to be able to analyse disruptions in supply chains more systematically, without relying on particular case studies, firm-to-firm level data would be needed for the EU as a whole. This type of data is not available at the moment of publication of this paper.

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Annex

The correspondence between each raw material and the codes in the trade data (CN8 codes) and the production data (PC8 codes) is done as follows.[29] First, we associate each raw material to the CN8 codes, based on existing European Commission documents.[30] Then, we associate the PC8 codes to CN8 codes, based on the correspondence table for CN2021 and PRODCOM 2019 from Eurostat RAMON. Table A1 summarizes the corresponding CN8 and PC8 codes for the raw materials of silicon-based designs of solar panels.

Table A1: CN8 and PC8 codes for raw materials relevant to solar panels

Prevailing designs materials	CN8 code	PC8 code
Silica	25051000	08121150
Gallium	81129289	24453073
Phosphorus	28047010	20132181
Boron	28045010	20132141
Tin	26090000 & 80011000	7291530 & 24431330
Lead	26070000 & 78011000	7291510 & 24431130
Silver	26161000 & 71061000	7291410 & 24411030
Indium	81129281	24453070
Molybdenum	26131000 & 2613900& 28257000 & 72027000 & 81021000	7291925 & 7291926 & 20121973 & 24101275 & 24453017

[29] CN8 stands for Combined Nomenclature at 8-digit level. PC8 stands for 8-digit Prodcom.

[30] European Commission, "Critical Raw Materials Resilience: Charting a Path towards greater Security and Sustainability" COM(2020)474 final.

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To Respond to the Pandemic, the Government Needs Better Data on Domestic Companies That Make Critical Medical Supplies

BY ERICA R. H. FUCHS, VALERIE J. KARPLUS, NIKHIL KALATHIL, M. GRANGER MORGAN

Real-time adaptive data collection capabilities could help policymakers guide decisions in the current health emergency and future crises.

Responding to a large-scale health emergency—such as the current COVID-19 pandemic—in a timely and efficient manner requires real-time data about the current state of manufacturing of critical medical supplies. Policymakers require such information to guide decisions to coordinate and mobilize additional capacity. Although existing public surveys—such as the Annual Survey of Manufacturers or the Economic Census—provide snapshots of US capabilities, they do not capture the rapidly evolving status of critical supply chains during a crisis. In addition, although the White House and entities such as the International Trade Commission can request information directly from companies, they are poorly equipped to do the frequent and comprehensive large-scale data collection needed to create a complete and accurate picture of an ever-changing situation. The result is that the US government is "flying blind," lacking the necessary knowledge of the nation's existing activities and capabilities to inform a policy response.

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How bad is the government's knowledge gap? To assess the potential scale of the gap on domestic manufacturing during the pandemic, we scraped data and did automated text analysis each week from Thomasnet, a leading North American Manufacturing industrial sourcing platform. Based on this data, we developed a list of firms that listed themselves as manufacturing face masks and N95 or other respirators, or the intermediate inputs needed therefore. We then corroborated this information and identified whether they were making the product of interest domestically, via additional searches on firm websites, filings with the Security Exchange Commission, data from D & B Hoovers, and interviews directly with companies.

Our investigation suggests that small- and medium-sized firms may be playing an important and poorly documented role in responding to the mask-and-respirator shortage associated with the pandemic. Even less well understood is the extent to which these and other firms could rapidly reorganize their production lines to meet newly pressing needs—as well as the sorts of policy actions and incentives that would work best to facilitate such a switch. To guide future policy decisions, including the coordination and mobilization of additional capacity, we recommend that Congress direct the US Department of Commerce to develop a strategy for the timely and adaptive assessment of US-based manufacturing capability of medical supplies for the duration of the present emergency, and document lessons to better support the creation of such an effort again in the event of a future emergency.

OVERLOOKED, UNDERUSED, AND UNKNOWN

Government sources of firm data are useful to measure economic activity and composition in a steady state, but are not designed to capture rapid changes during emergencies. Currently, no public or proprietary data sources capture in real time the evolving universe of firms involved in supplying the US medical supply market. Once every five years, the US Census Bureau conducts the Economic Census, which captures all manufacturing plants in the economy (250,000+ plants). The survey and data collection methods are world class, but it can take more than two years to publish the results. The most recent Economic Census is from 2017. Summary data were released only in fall 2020, and additional data will be released on a flow basis through December

2021. The Annual Survey of Manufacturers is published more frequently, but is skewed toward the largest manufacturing plants (around 45,000 facilities). The survey was conducted in 2018 and published in April 2020. In addition, very few sources include reliable data on plant location and production capacity, and coverage within these is sparse.

Previous work by Michael Gort and Steven Klepper and others used information from the Thomas Register of American Manufacturers to compile annual data on US-based producers of specific products. Similarly, we turned to Thomasnet to identify firms that manufacture masks, respirators, and their intermediate inputs in the United States.To begin to assess the consequences of spotty real-time data, we leveraged weekly web scraping and automated text analysis of Thomasnet to identify firms that self-identify as having domestic manufacturing of masks, respirators, and their intermediate inputs (see Figure 1). As categories are not precisely defined and firms may use different rules when reporting information to Thomasnet, we then checked the data against searches on the websites of various firms, information from D & B Hoovers, and interviews directly with companies. Here, particularly important was clarifying which Thomasnet-listed firms had domestic manufacturing facilities of the target medical supplies.

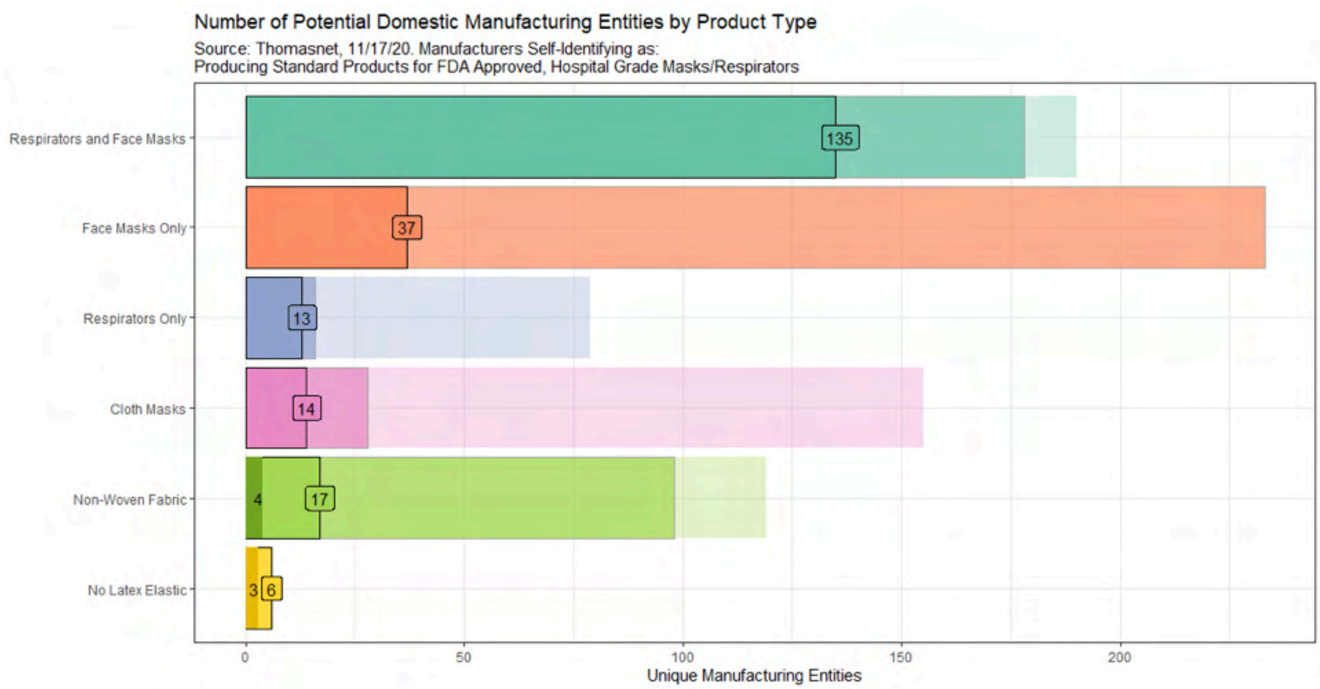

Figure 1: Thomasnet-Listed Manufacturers of Masks and Respirators and Intermediate Inputs Self-Identify as Producing Standard Products for FDA-Approved, Hospital-Grade Masks and Respirators.

Figure 1 displays the results of our Thomasnet data collection and categorization algorithm. The faintest bars are the total number of manufacturing entities listed on Thomasnet as offering our target products (as listed on the y-axis). The faded bars are the number of manufacturing entities listed on Thomasnet that self-identify as serving the medical market or as matching our definition of meeting technical requirements for hospital grade masks and respirators. The outlined sections with the darkest *coloring and a number show the subset of firms on Thomasnet with self-listed text that meets our definition for producing standard products for FDA-approved, hospital-grade masks or respirators.*

As of November 16, we found that 56 Thomasnet-listed firms produced a product of interest at a domestic manufacturing facility. Forty-four firms manufactured respirators, masks, or both; seven manufactured nonwoven fabrics used in medical-grade masks; and five made nonlatex elastics. We were able to confirm exact geographic locations of plants for 32 of these 56 companies—information that may prove particularly helpful to local representatives in both federal and state governments as they respond to the pandemic. Our real-time data confirmed that the number of domestic manufacturers of each of these products has been increasing since the start of the pandemic.

Currently, no public or proprietary data sources capture in real time the evolving universe of firms involved in supplying the US medical supply market.

Comparing the Thomasnet data with White House data suggests substantial overlooked capacity. Of the 44 Thomasnet facilities producing respirators or masks domestically, only three are among the five largest firms (3M, Owens and Minor, Honeywell, Moldex, and Prestige America) that were used in White House estimates of production capacity in the early phase of the pandemic. Furthermore, our limited view from Thomasnet suggests that small- and medium-sized enterprises may be playing an important, albeit poorly documented, role in responding to mask and respirator shortages associated with the pandemic.

To support firms that are attempting to respond to the pandemic, whether by opening or repurposing domestic facilities, policymakers must first identify and develop an understanding of the universe of firms making such decisions. For example, three out of eight of the 44 Thomasnet companies for which we were able to find capacity information had recently purchased equipment to make masks or respirators in the United States. It's unclear, however, to what extent these firms may be able to achieve their theoretical capacity.

An anecdote from a medium-sized US medical supply company illustrates the type of challenges these companies face in reshoring and pivoting to new products. Shortly before the pandemic, the company had imported enough equipment from China to manufacture 9 million ASTM Level 2 masks per month. The company planned to provide the masks at cost for the duration of the pandemic. With the pandemic in full swing, the company's colleagues in China supported it in getting the equipment up and running. However, inability to gain access to a number of material inputs prevented the company from running at capacity.

Comparing the Thomasnet data with White House data suggests substantial overlooked capacity.

The company's most challenging bottleneck was obtaining elastic for the ear loops, and not the highly publicized and technically challenging melt-blown polymer used in the mask itself. The elastic needed to be latex-free, come in a precise width and elasticity (stretchiness), and be available in bags to work in the automated machines. The company eventually found a domestic supplier for some of the necessary elastic, but that firm wasn't able to provide the elastic at sufficient scale for 9 million masks. Furthermore, that firm's elastic came on a spool, so for an extended time workers had to unspool the elastic by hand, with the associated productivity slowdown one would expect. By collecting data on capacity versus production, it would be possible to identify firms facing such challenges achieving their capacity—whether due to regulation, intermediate input supply, labor, critical technical knowledge, or otherwise. In addition, being able to adaptively add questions as awareness of issues change—for example, about challenges companies are facing—could further guide policymakers.

Our searches on firm's websites, triangulation with data in D & B Hoovers, and interviews with companies allowed us to identify which firms are manufacturing domestically, and to understand what aspect of their production is actually domestic. Identifying what challenges may exist that prevent a company from moving manufacturing to the United States is an equally complex task. For example, Fulflex is a Thomasnet-listed manufacturer of latex-free elastics and nonwoven fabric, located in Brattleboro, Vermont.Fulflex serves a global market, and primarily relies on international production networks in Singapore and India to manufacture its products. Currently, Fulflex has domestic manufacturing capabilities, but they operate with much longer lead times than international facilities. As a consequence, while the company shows up in the figure as a domestic manufacturer of latex-free elastic (the blue group in Figure 2), the majority of that production occurs overseas.

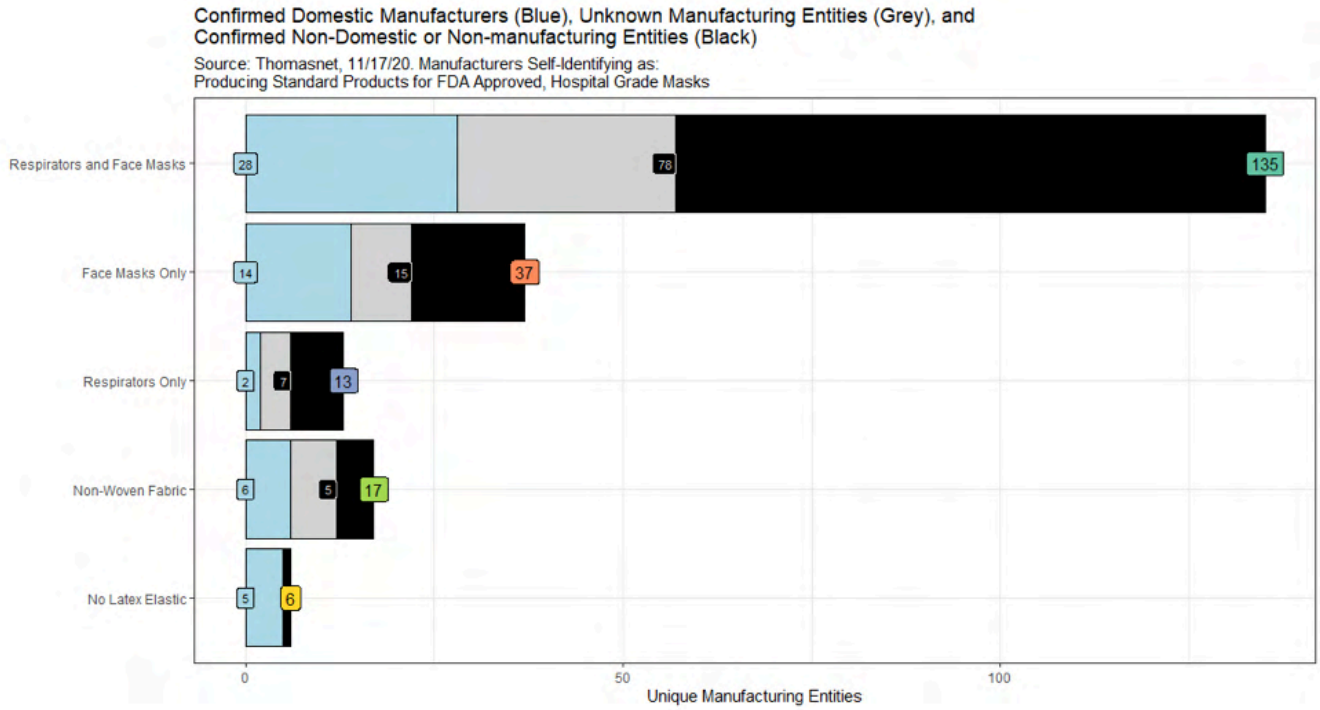

Figure 2: Domestic Manufacturing Breakdown of Thomasnet Listed Manufacturers of Standard FDA Approved Hospital Grade Masks/Respirators.
"Unique Manufacturing Entities" on the x-axis represents firms that self-identify on ThomasNet as a manufacturer of standard FDA-approved, hospital-grade masks and respirators on November 17, 2020. The blue portion of the bar is the number of firms with confirmed production facilities in the United States. The black portion of the bar is the number of firms confirmed as a non-domestic or non-manufacturing entity. The grey portion represents companies whose production location we have yet to confirm.

Similarly, the Moore Co Textile Group is a leading manufacturer of elastic with a large selection of orthopedic and medical elastics (both pre-COVID and since the onset of the pandemic). Their primary manufacturing facilities are located in El Salvador, under an El Salvadorian division of the company. The US branch of this company consists of a "network of contract manufacturers that produce uniquely designed and qualified narrow elastics and webbings." Through this network, the company can produce a product that qualifies under the Berry Amendment, which requires the Department of Defense to give preference in procurement to domestically produced, manufactured, or home-grown products. The Moore Co Textile Group currently does not count as a domestic manufacturer, but it may be well-placed to scale up domestic manufacturing in response to COVID-19, and also able to speak to the challenges of scaling-up domestic manufacturing. Here again, real-time adaptive data collection capabilities could support policymakers in changing the information sought so as to better understand what percentage of a firm's intermediate inputs and final products are sourced domestically, the challenges these firms face in manufacturing domestically, and in asking direct questions about such challenges.

Thomasnet also offers a way to search for firms operating in closely relevant product spaces, and who thus may have the potential to pivot into addressing pressing needs. As of November 17, 185 firms described themselves on Thomasnet as being manufacturers of FDA-approved or hospital-grade face masks or respirators, a further 17 said they manufactured the melt-blown or spunbonded fabrics necessary for hospital-grade masks or respirators, and six manufactured no-latex elastic. An additional 250 firms described themselves as making masks, respirators, nonwoven fabrics, or latex-free elastic and listed themselves as serving medical markets or manufacturing products that would likely meet technical specifications for a hospital-grade face mask (243 mask or respirator firms and 7 nonwoven fabric firms). Further research would be required to understand which of these additional firms are already making hospital-grade masks or the intermediate inputs, which are trying to but facing challenges, and which are not yet producing medical supplies but with the right incentives and support might do so.

As demonstrated above, real-time adaptive data collection capabilities could revolutionize the ability of policymakers to understand the complete universe of domestic firms: which are already making hospital-grade masks or the intermediate inputs therefore, what challenges they face, and which are not yet producing medical supplies to meet pressing needs but presented with the right incentives and support might pivot to do so. This information is essential to guide decisions to coordinate and mobilize additional capacity in a health emergency or other crisis.

BLUEPRINT FOR ACTION

Congress should direct the US Department of Commerce to develop a strategy for timely and adaptive data collection of US-headquartered and US-located COVID-19 medical supply manufacturing capabilities for the duration of the emergency and document lessons that will allow the government to better support the creation of such an effort again in the event of a future emergency.

Real-time adaptive data collection capabilities could revolutionize the ability of policymakers to understand the complete universe of domestic firms.

The real-time data collection effort should include collecting information on the current production capacity of these companies in emergency-relevant intermediate inputs and final products. In addition to capacity, real-time data should be collected on actual production volumes in order to identify possible bottlenecks—regulatory, material, labor, knowledge, or otherwise—that are preventing firms from leveraging their full capacity.

Furthermore, it is essential for the data collection effort to be set up such that government agencies can easily adapt what information is collected. For example, as analysts learn about differences between equipment capacity and actual production, they may add questions about the obstacles that companies face in fully achieving their capacity. Or as analysts learn about complexities in domestic sourcing, they might seek information about what percentage of a firm's intermediate inputs and final products are sourced domestically and the challenges it faces in manufacturing domestically. By combining this domestic production capability data with other readily available information (such as collected by Johns Hopkins University, the US Centers for Disease Control and Prevention, and the US Department of Health and Human Services), local, state, and federal governments can develop more informed demand-side and supply-side policies to address gaps in a rapidly changing context.

Aggregate information on gaps between capacity and demand as well as on common challenges or bottlenecks should be communicated through a real-time dashboard to inform both the public and private sector. Along with the overall data collection effort, the dashboard would increase transparency, providing real-time information on where additional production and bottleneck-reducing innovations may be most valuable.

Finally, the Department of Commerce's data collection and analysis activity must have a sunset clause such that it ends when the pandemic does.Ending the real-time data collection effort at the end of the pandemic will avoid continued expense without equivalent need (e.g., the rapidly changing environment of a pandemic is not the same as nonemergency periods). As part of the sunset clause, the individuals leading the effort should be required to systematically document lessons learned both for "steady-state" activities as well as for future crises. Here, future crises should include not just pandemics, but also natural disasters, war, and other undertakings where timely and adaptive collection and analysis of data may be essential to inform government decisions.

In responding to Congress's mandate, the Department of Commerce should consider leveraging:

- Automated, large-scale data collection and analysis via market intermediaries of registered transactions.
- The US Census Bureau's survey capabilities as well as its Registrar of Businesses, with a similar approach and (most importantly) speed as was achieved for the COVID-19 Small Business Pulse Survey.
- A public-private partnership that brings together the large-scale data collection and analysis capabilities available in academia and industry (e.g., Google, Microsoft, or Amazon) with government entities that have access to or are seeking to act on this information.

- The National Institute of Standards and Technology, given its existing role leading Manufacturing USA (formerly, the National Network of Manufacturing Innovation Institutes) as well as governing the Manufacturing Extension Program.

By combining this domestic production capability data with other readily available information governments can develop more informed demand-side and supply-side policies to address gaps in a rapidly changing context.

The data challenges hindering government decisionmaking under the current COVID-19 crisis are not unique. Agencies as diverse as the US Departments of Defense, Commerce (including the Economic Census and International Trade Commission), Transportation, Energy, and Homeland Security (including the Federal Emergency Management Agency) can benefit from harnessing emerging state-of-the-art data collection and analytics capabilities. Whereas the *Artificial Intelligence (AI) in Government Act of 2019* (S. 1363) creates a new office in the General Services Administration "to promote adoption, use, competency, and cohesion of Federal Government applications of artificial intelligence (AI) to enhance productivity and efficiency of government operations for the public benefit," those efforts are still in their infancy.

Achieving the goals of this legislation will take a long time, with many obstacles and lessons learned. A 2018 report from the MITRE corporation unpacks how intra- and intergovernmental actions and knowledge pertaining to critical supply chains are uncoordinated and isolated from each other. Further, a 2020 report by Kathy Stack, formerly of the Office and Management and Budget, demonstrated how government programs underperform because of challenges integrating data across agencies and levels of federal, state, and local government. Tackling these obstacles alone will be challenging. Even more ambitious initiatives might be able to leverage machine learning and novel data collection and analytics to tackle much more challenging pressures, such as strategic opportunities and weaknesses versus other nations. (In the inaugural session of the National Academies' study on Science and Innovation Leadership for the 21st Century, representatives from the DOD's Defense Advanced Research Projects Agency and the Strategic Technology Protection and Exploitation Office both said that they lacked the mechanisms and ability to assess their strategic weaknesses and opportunities versus other nations in technologies critical to national security.) Assuming our proposal is adopted, the information collected and analyzed and lessons learned from ramping up real-time data and analytics capabilities during the COVID-19 emergency will offer important lessons for future government responses to a wide variety of crises.

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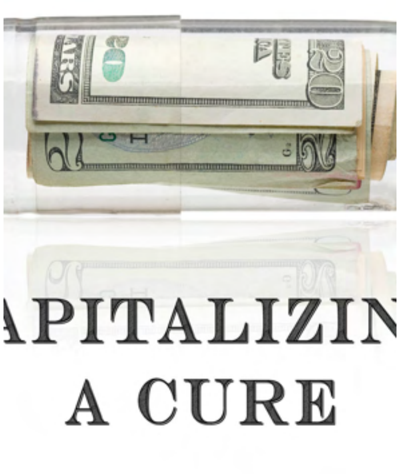

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Original Article

OXFORD

Short-term economic dynamism as a policy tool to address supply shortages during crises

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Abstract

This paper investigates the role of short-term economic dynamism in responding to crisis induced supply shortages. We focus on the domestic manufacturing ramp-up of surgical masks, respirators, and their intermediary products in response to the COVID-19 pandemic. We develop a novel method for timely identification and validation of the evolving state of domestic manufacturing. To unpack the activities of domestic manufacturers and related institutions, we triangulate across 56 qualitative interviews, certifications, Thomasnet.com®, industry associations, and other public data. We find that while large manufacturers could rapidly scale up, onshore, or diversify production to enter into domestic production of critical medical supplies, these large manufacturers alone were insufficient to meet the spike in demand. In face of this shortage, small and medium enterprises (SME), who entered into mask and respirator production as de novo firms, spin-offs, and by diversifying, were important in increasing overall domestic capacity and serving markets unmet by large hospital distributors. These firms often had fewer competencies and resources compared to larger firms, and received less effective government support. Despite these disadvantages, a number of SMEs succeeded in entering into domestic production, and our interviews suggest this capacity could have been better integrated into the national response. We propose new theory for how and when federal and state governments should support short-term economic dynamism (firm entry into target products and/or markets) during crises to address supply shortages, and the types of market and network failures federal or state governments may be most effective at addressing.

JEL classification: L52, O25, R11

1. Introduction

During crises, nations need reliable and timely access to critical supplies, especially health and safety-critical products. Traditional approaches have been to stockpile resources, leverage existing domestically owned incumbents to ramp-up production, or use the US Defense Production Act (DPA) to engage a wider variety of firms in production activities. The COVID-19 pandemic, however, offers a case study of a fourth option: relying on *short-term economic dynamism* in the form of scale-up and new entry by diversifying and *de novo* firms The institutions that support such *short-term economic dynamism* in response to sudden and potentially temporary supply shortages are poorly understood, particularly in the case of small- and medium-sized enterprises (SMEs).

Our research leverages the case of firm entry into US domestic surgical mask and respirator production during the global COVID-19 pandemic to shed new insights into *short-term economic dynamism* and the policy tools that may be able to support such dynamism during crises. We create a novel dataset through weekly web scraping of Thomasnet.com® supplier listings of market participants in the surgical-grade mask and respirator market, manually validate which of these companies set up a US domestic manufacturing location to produce surgical masks/respirators, and cross-reference these participants with National Institute for Occupational Safety and Health (NIOSH) and Federal Drug Administration (FDA) regulatory approvals, along with federal contracts and industry association databases. We pair this near real-time information on domestic production with 56 open-ended exploratory interviews with companies that entered into the production of masks and respirators, as well as entities that participated in this production ecosystem (such as regulators at the FDA/NIOSH, state governments, NIST Manufacturing Extension Partnership [MEP] centers, nonprofits, and consultants).

We find that while large firms may excel at rapidly expanding production and entering into regulated markets to alleviate severe shortages, large-firm entry alone was insufficient to satisfy all demand in a timely fashion given the expected loss of life and a potentially short window of public willingness to act. Our results further emphasize how diversifying and *de novo* SMEs were sometimes able to contribute substantially in alleviating severe shortages. That said, SMEs struggled to break into existing markets and faced challenges related to funding, delays and costs of regulatory certification, access to machines, and commercialization of novel products. We unpack ways that federal and state governments can support firm entry of different types during crises and discuss gaps in those responses. We propose a new theory for how federal and state supporting roles can be used to better leverage the full variety of firm entry during a crisis, and how these roles may need to differ depending on firm size, relevant capabilities, and the intensity of demand shortages.

2. Prior literature

2.1 National supply chain resilience during crises

Nations need reliable and timely access to critical supplies during crises such as geopolitical conflict, pandemics, and natural disasters to ensure national defense, economic security, and public health. The existing academic research and policy reports on the role of the federal government in ensuring access to critical supplies during crises focus on stockpiling critical products for which access has a high expected value (Mason, 2011; Ajao *et al.*, 2015; Huang *et al.*, 2017), leveraging the US Defense Production Act (DPA) to increase the scale of production (Congressional Research Service (2020a)) and the role of government in disaster coordination response (Chen *et al.*, 2008; Nolte *et al.*, 2012; Ishiwatari, 2021). Missing from this playbook is a discussion of how governments may be able to leverage *short-term economic dynamism*—the entry of firms of all sizes into product spaces experiencing shortages—to alleviate shortages.

Operations research and decision science scholars have used decision trees and other modeling methods to estimate optimal stockpiling amounts and inventory management (especially for goods that deteriorate) (Maddah *et al.*, 2014; Zhou and Olsen, 2017).[1] At the same time, stockpiling has a cost, in that it can be difficult to know in advance what goods will have shortages, and stockpiled goods can expire over time. In contrast to stockpiling, which involves the management of *pre-crisis* inventories of specific *products*, the US DPA offers a tool to influence *domestic manufacturing capabilities*—both strategic assurance of domestic manufacturing capabilities pre-crisis and the scale-up of capabilities to address shortages *during crises*.[2] Given the

[1] The Strategic National Stockpile Division, which is housed in the Center for Disease Control, plays a role in acting as a national supply commons (Handfield *et al.*, 2020) and in coordinating and communicating with partners across the supply chain both before and during crises (National Academies of Sciences, Engineering, and Medicine, 2018; Congressional Research Service, 2020b).

[2] The DPA provides three forms of presidential authority to assure domestic manufacturing of critical products: (i) voluntary agreements with private industry, including the blocking of foreign mergers, acquisitions, and/or takeovers, and employment authority; (ii) expansions of supply, authorizing the use of loans, loan guarantees, direct purchases, purchase commitments, and federal procurement authority to incentivize the expansion of a domestic industrial base;

Possible Strategies:	Pros:	Cons:
Stockpile Resources	• Ready access to supplies if needed • Strategic restocking can support industrial base	• Opportunity cost • Supplies expire • Ill-matched to novel needs • May be insufficient in scale
Rely on established firms making product	• Expert, trusted sources • May be able to respond quickly (stress tests) • Defense Production Act	• International supplies may be inaccessible (e.g. global shortages, geopolitical crises) • Dependency on select firms • Existing scale(-up) insufficient
Foster *Short-Term Economic Dynamism* - Existing Companies - De Novo Firms	• May add capacity • May diversify the source of supply, reduce market or geopolitical power issues • Novel ideas, approaches	• Unvalidated sources • Difficult to coordinate • Time delay in starting or scaling up new production

Figure 1. A summary of the strengths and weaknesses of various strategies for ensuring access to critical medical supplies during a global public health crisis. The focus of this research paper is on the lower two options

cascading set of recent supply chain crises during and after the COVID-19 pandemic, a host of operations researchers have been proponents of the value of stress testing existing producers during noncrises. This research argues that scale-up capabilities of existing firms can be both better understood and actively fostered in advance of a crisis (Simchi-Levi *et al.*, 2014; Simchi-Levi, 2015), which could provide the nation with important information on time to recover—how long it takes a specific node to come back online after a failure—and, time to survive—how long the supply chain can satisfy demand after a node goes offline (Simchi-Levi and Simchi-Levi, 2020). Notably, stress testing requires a data infrastructure and data transparency, which may be costly and difficult to assemble, especially in the context of millions of firm-to-firm connections and dependencies (Dai *et al.*, 2020; RAND, 2021; Ivanov and Dolgui, 2022). Finally, similar to stockpiling, while known capabilities and having on-hand idle equipment in select critical defense and health products will have a high expected value, it can be difficult to predict the full set of products that will be demanded by the next crisis.

A third option, not discussed widely in the literature but which happened organically during the COVID-19 pandemic, is to leverage *short-term economic dynamism*—*de novo* firm entry and existing firm diversification alongside incumbent firm scale-up—during sudden shortages. Market-driven entry by *de novo* and existing firms diversifying into new markets holds the potential to offer additional capacity, diversification of supply, and introduction of novel ideas and approaches. However, such entry takes time, can be difficult to coordinate, and involves potentially unvalidated sources. These factors raise the question of the appropriate role of government in fostering such dynamism, both pre-crisis and in real time.

The portfolio of strategies for a nation seeking to ensure access to critical supplies in response to sudden shortages or spikes in demand is summarized in Figure 1. We focus in this paper on policy tools to support *short-term economic dynamism* to alleviate shortages *during* crises.

2.2 Economic dynamism: firm entry and exit

The concept of economic dynamism is primarily discussed over the long term, in the context of Schumpeterian cycles of creative destruction, business cycles, and product life cycles. These discussions examine the relationship between firm entry, exit, expansion, and contraction and long-term productivity and growth, competition, and investment in the United States (Decker *et al.*, 2014; Gordon, 2016; Agarwal and Gort, 2002; Gutiérrez and Phillippon, 2017). Researchers have also explored the role of supporting institutions in facilitating entrepreneurship and contributing to long-term cycles of economic dynamism (Braunerhjelm and Henrekson, 2013). Related to this literature, a large body of research has focused on firm entry and exit over

and (iii) priorities and allocations, in which the President can require companies to prioritize and accept contracts for specific goods and services (Congressional Reserach Service, (2020a)).

technological change and discontinuities, including in response to industry-disrupting technologies (Christensen, 1997) and over industrial and product life cycles (Gort and Klepper, 1982; Klepper and Graddy, 1990; Agarwal and Gort, 1996; Klepper, 1996, Klepper and Simons, 2000; Agarwal and Bayus, 2002; Klepper, 2002). To date, less has been written on shorter-term economic dynamism in the context of crisis-induced demand spikes and/or supply shortages. To describe this type of response, we coin the term *short-term economic dynamism*.

With the advent of the COVID-19 pandemic, a new body of research has begun to emerge, examining patterns of business entry and exit during the pandemic. To date, this work has described aggregate patterns of firm entry and exit during the pandemic (Decker and Haltiwanger, 2022; Verlhac *et al.*, 2022). Similar to past work on economic downturns (Cefis and Marsili, 2005; Goldfarb and Xiao, 2017), Muzi et al. find a negative correlation between firm productivity and innovation, and firm exit during COVID-19 (Muzi *et al.*, 2021). Likewise, Costa et al. find that firm pre-pandemic organizational histories are predictive of firm dynamism during the pandemic (Costa *et al.*, 2023). Lacking, however, has been the possibility of governments leveraging and facilitating short-term economic dynamism—specifically *de novo* or diversifying firm entry—to alleviate specific product shortages during the corresponding sudden spikes in demand and/or simultaneous disruptions in supply.

2.3 The role of government in supporting manufacturers

The existing literature on the government's role in supporting manufacturers (especially SME manufacturers) focuses on support for responding to new technology and organizational paradigms and speeding up the dissemination and adoption of the latest process technologies (MacDuffie and Helper, 1997; Hsu and Chiang, 2001). This literature unpacks the government's role in facilitating and encouraging collaborative relationships between and among manufacturers and suppliers to facilitate learning and upgrading, as well as network formation (Whitford and Zeitlin, 2004; McEvily and Marcus, 2005; Whitford, 2005; Brandt and Whitford, 2017; Brandt *et al.*, 2018). With the exception of Reynolds et al. (2021), whose working paper studies Massachusetts state investments for ramping up PPE, the literature offers little guidance on the appropriate role of government facilitation and/or support for short-term economic dynamism during crises, including strategies for the rapid identification and mobilization of relevant SMEs (Whitford and Zeitlin, 2004; Helper and Stanley, 2007) and the appropriate role for federal vs. state actors (Singerman, 2020).

3. Background: surgical masks and respirators before and during COVID-19

The COVID-19 pandemic caused an unprecedented spike in global demand for medical supplies and created shocks across global supply chains. As of May 2020, over 6000 organizations across the United States requested PPE, with more than 8000 requests for surgical masks and N95 respirators (Gondi *et al.*, 2020). That same month 87% of nurses surveyed in the United States reported reusing a surgical mask or respirator, while 27% of nurses reported interacting with COVD-19 positive patients without appropriate Personal Protective Equipment (PPE).[3] To ensure access to supply, many countries began restricting exports and seeking to boost domestic production of surgical masks and respirators across multiple supply chain bottlenecks in the global value chain (OECD, 2020; World Trade Organization, BDI, 2020).

3.1. Product and manufacturing

Surgical masks and respirators (see images, top of Figure 2) protect the wearer from interacting with harmful particles (OSHA, 2015). In contrast to surgical masks, respirators provide an extra layer of protection by forming a tight seal to filter the *entirety* of the air a wearer breathes. Surgical masks and respirators are manufactured using highly automated machinery that ultrasonically welds different layers of nonwoven fabric together. Surgical masks consist of up to three layers

[3] See National Nurses United (2020).

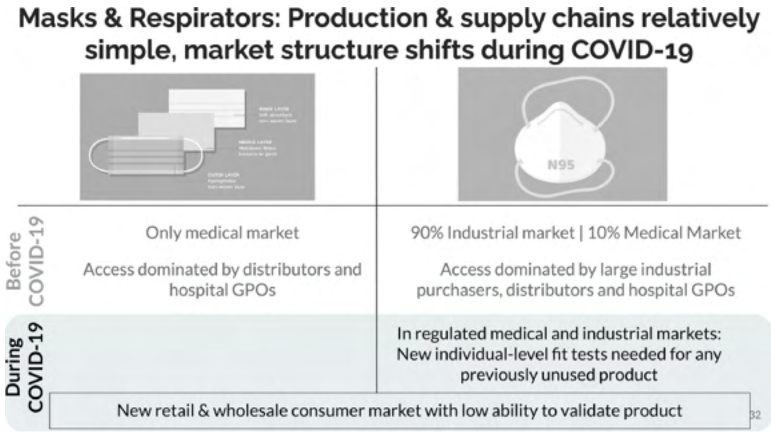

Figure 2. A comparison of surgical masks and respirators, and their markets. These devices involve relatively simple supply chains and production processes, but the market structure shifted fundamentally during the COVID-19 pandemic

of nonwoven fabric, and the standard design for surgical masks involves two layers of cheaper and more comfortable spunbonded nonwoven fabric surrounding one layer of fine-fiber electrostatically charged melt-blown fabric.[4] Respirators consist of the same general components but involve four or five layers of fabric.[5]

3.2 Market pre- and post-pandemic

Before the pandemic, *surgical masks* were almost exclusively used in the medical market. In 2019, the monthly market for surgical masks was 108–140 million masks, with domestic suppliers producing 17 million (15% of the US market) surgical masks per month and imports providing an estimated 85% of the US market.[6] For *respirators*, 90% of pre-pandemic sales were for industrial and construction settings, with only 10% going to the medical market. Prior to the pandemic, total N95 demand in 2019 was estimated at 445 million units annually. Domestic respirator production in 2019 was estimated at 30M respirators per month. For both surgical masks and respirators, access to medical markets was (and is) dominated by large distributors and hospital group purchasing organizations (GPOs). In addition, in regulated settings (e.g., construction, industrial, and medical), respirators must pass individual basis fit tests ranging in cost from $30 to $50 per person, with any new or previously unused products needing to pass new individual-level fit tests for regulated use both before and during the pandemic.[7]

Demand for respirators and surgical masks increased by over an order of magnitude during the pandemic. Demand for surgical masks more than tripled, increasing to between 370 and 430 million masks per month, not including the market for high filtration disposable masks used in nonregulated settings by hospitals, clinics, manufacturers, utilities, other businesses, and the public, as described in Figure 2.[8] In addition, there were 1.6 billion imports of respirators between July and September of 2020 alone, not counting domestic production.

4 See Chellemani et al. (2013).

5 The highly automated machines that manufacture respirators are substantially more expensive than those that manufacture surgical masks (pre-pandemic respirator machine: $300,000+; pre-pandemic surgical mask machine: $15,000–$30,000).

6 See USITC (2020).

7 See RPB Safety (2021) and Occupational Safety and Health Administration (OSHA) (n.d.).

8 See USITC (2020).

	Surgical Masks		Respirators	
	Pre-pandemic	**During COVID-19**	**Pre-pandemic**	**During COVID-19**
Product Standards	Set by ASTM, Tested in Certified Labs: BFE, PFE, Breathability, Fluid Resistance, Flammability			
		New Non Medical (2/21)		
FDA 510K	**(Up to $65,000)** Tests for 32 masks	**($70,000-$120,000+)** Tests for 96-160 masks	Run through NIOSH since 2018: Engineering, quality system, and post-market review	
FDA EUA		(August 5th, 2020) Test results No sample		Allow medical use of industrial respirators, foreign standards (e.g KN95, KF94), and respirator reuse (March, 2020) (discontinued: 6/21)

Figure 3. A summary of standards that must be met by surgical masks and respirators. These standards are set and must be certified by a third-party lab. Medical market entry is challenging and regulated by the FDA and NIOSH

3.3 Product standards and regulation

Product standards for surgical masks and respirators remained unchanged during the COVID-19 pandemic.[9] NIOSH did not substantially change their review process and continued reviews that focused heavily on production and process. In contrast, for surgical masks, the FDA implemented several changes to the regulatory approval process. The FDA issued an Emergency Use Authorization (EUA) for approval of surgical masks on August 5, 2020 intended both to help classify new devices appearing on the market and to simplify the approval process.[10] In October 2020, concerned about the quality of primarily imported products, the FDA increased the number of mask samples required for FDA 510k certification, thus raising the cost of surgical mask certification during the pandemic.[11] This increase in the testing sample size for masks increased the cost of regulatory approval from a maximum of $65,000 to between $70,000 and $120,000, or higher in certain situations.[12] These shifts are summarized in Figure 3.

4. Methods and data

We triangulate data (Jick, 1979) from industrial data sources (Thomasnet.com® supplier listing and industrial associations), regulatory approvals, government contracts, state government databases, 56 qualitative interviews, and archival data (news articles about companies and states, and state and company websites). Our data sources and their purpose are summarized in Table 1. These data identify domestic manufacturers participating in mask and respirator production over time. Our qualitative interviews provide insights into the experiences of firms who entered into the production of masks and respirators, the processes by which they entered, as well as those of the external actors (states, nonprofits, and corporate partners) who interacted with these firms.[13]

4.1 Data triangulation and sample

No single database covers the entire set of domestic manufacturing of surgical masks, respirators, and their intermediary products. Our sample includes all of the dominant top five major

[9] Surgical masks and respirators are evaluated against five product standards set by ASTM International. Companies submit samples of their products to accredited testing labs to be evaluated against these five dimensions and then submit test results for regulatory approval. As Class II medical devices, companies must obtain an FDA 510K certification to manufacture surgical masks and respirators. This certification ensures a company's products meet specific standards prior to marketing and requires quality assurance for each product line and manufacturing location. In 2018, NIOSH took over responsibility for the regulation of surgical *respirators* (but notably not also surgical masks) from the FDA (FDA MOU 225-18-006).

[10] Congressional Research Service, 2020c; FDA Regulator Interview, October 18, 2021.

[11] See FDA (2021).

[12] See USITC (2020).

[13] Finally, we began a survey of mask and respirator manufacturers and used the preliminary results of this survey to complement our interview responses.

Table 1. Data sources, types, and purpose for the quantitative and qualitative data used.

	Data type	Data source	Purpose
Quantitative	Industry participation	Web-scraped data and text of Thomasnet	Identify domestic manufacturers over time
		Public news, phone calls, and websites; regulatory approvals, industry association membership (AMMA)	Validate (product and domestic manufacturing) and expand sample; industrial context
	Firm details and outcomes	FDA 510K database; FDA EUA database; NIOSH approval database	Application date (FDA 510K only); approval date; aproned product; listed firm location
		Federal government contracts (USA Spending)	Contract solicitation date, contract award date, contract product, contract dollar amount, awarding agency, listed firm location
		D&B Hoovers' firmographic data	Annual sales, annual employees, corporate network, listed firm location, factory sq. ft.
Qualitative	Stakeholder experiences	56 interviews: companies who entered (defined as standing up a US domestic plant and making sales), state and federal actors, consultants, industry, associations, industry observers, and nonprofits	Identify processes and characteristics that enable entry, inform survey questions
		Firm websites, news articles, survey responses	Triangulate firm processes and characteristics for 20 mask and respirator end-product manufacturers

producers, as well as *de novo* firms, and firms that diversified to enter the mask/respirator market. As illustrated in Figures 4 and 5, by triangulating data across multiple public and private data sources, we were able to construct a more complete sample of firms that manufactured these products during the pandemic.[14] Our quantitative data are primarily derived from weekly (May 30, 2020 to September 7, 2021) scraping of Thomasnet.com®[15] (a leading North American Manufacturing industrial sourcing platform) in order to identify and catalog firms that self-identify as manufacturing masks, respirators, and their intermediate inputs. We complemented these data with searches on firm websites, news reports, and phone calls to manually validate manufacturing capabilities and location (Fuchs *et al.*, 2020).

To build a more complete sample of firms that entered into the manufacturing of masks and respirators, we added data from industrial associations (the American Mask Manufacturers Association [AMMA]), regulatory approvals from the FDA and NIOSH, and federal government purchases of PPE during the pandemic (USAspending.com). We matched firms through Data Universal Number System numbers and obtained additional firmographic information from the D&B Hoovers database (however, not all firms in our sample were listed on D&B Hoovers).[16] These

[14] Importantly, while we attempted to be as thorough as possible, this representation does not capture the full universe of firms that have pivoted, as some firms may have bought machines and never incorporated or announced a change.

[15] Previous academic work (Gort and Klepper, 1982; Jovanovic and MacDonald, 1994; Klepper and Simons, 2000; Agarwal and Bayus, 2002; Klepper, 2002; Agarwal and Bayus, 2007) has utilized the Thomas Register of American Manufacturers to compile annual data on US-based producers of specific products. These papers supplement data from the Thomas Register with other sources, such as data from the firms, to study firm entry, exit, and the evolution of market structures.

[16] The AMMA was formed in late 2020 to bring together small manufacturers of face masks and respirators and advocate for their needs at the state and federal levels. The FDA and NIOSH databases contain information about companies that are approved to sell products that have been vetted and certified by these agencies (as discussed in Section 3.3) The FDA database is downloadable by the public, and we web scrape NIOSH approvals to collect those data. Finally, federal government agency purchases of PPE for internal use or distribution are publicly available at USA Spending.

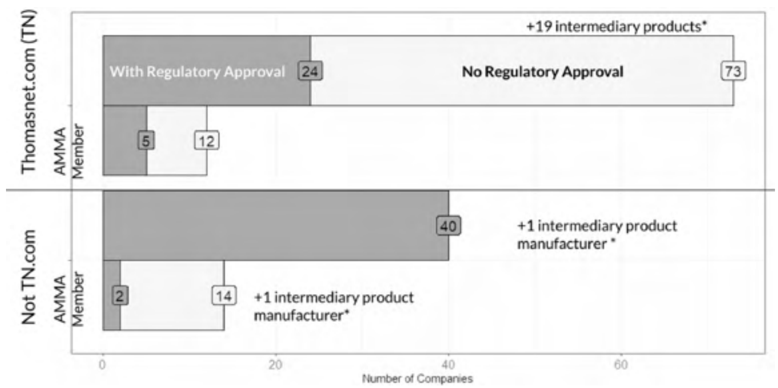

Figure 4. A summary of firms in our sample that did and did not obtain regulatory approval across the different databases we use. The industry sample of firms that have entered into the production of surgical masks, respirators, and their intermediary products is difficult to identify and split across multiple public and private data sources. The number and percent of firms interviewed of each type are in parentheses

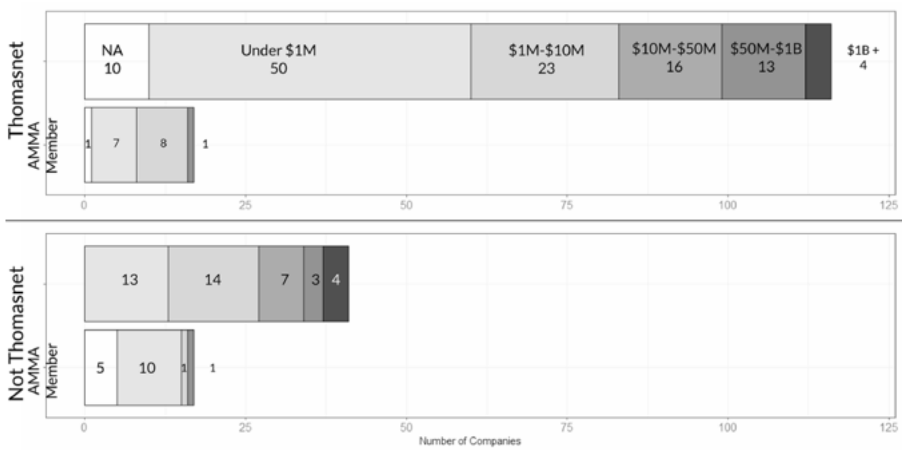

Figure 5. A summary of firms in our sample by the firm size. AMMA firms tend to be smaller, but a substantial number of the firms that we identify as validated domestic manufacturers are SMEs, although large firms are well represented in both the Thomasnet.com® and non-Thomasnet.com® samples

databases all add further detail but are biased in that they only offer information about firms that received government contracts, obtained regulatory approval, or actively joined industry organizations. Out of a total sample of 192 firms, we interviewed 36, or 14%.

4.2 Interviews

We conducted 56 open-ended interviews totaling nearly 60 h between January 2021 and October 2021. We made efforts to contact all validated domestic manufacturers of masks, respirators, and their intermediary inputs from Figure 4 and in this way were able to obtain responses from a representative subgroup of domestic public, private, and nonprofit actors relevant to the industry, including government, industry association, purchaser, and industry observers, in addition to manufacturers. Figure 6 summarizes these interviews. Our interview group is representative of our broader sample of 192 firms on two metrics: size and regulatory approval status. We concluded our interviews upon reaching a point of theoretical saturation, where firms and other institutions continued to provide largely the same answers based on their size, capabilities, and competencies.

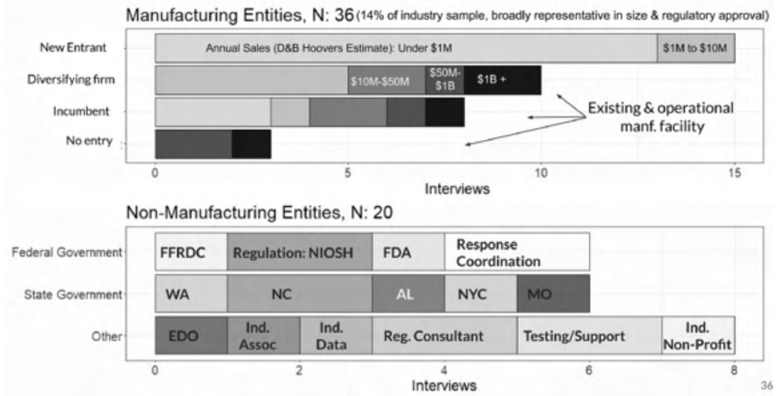

Figure 6. A summary of firms in our sample by manufacturing and non-manufacturing entities. We conducted 56 interviews between January 2021 and November 2021 with entities from across the surgical mask and respirator manufacturing ecosystem. Our interview sample of firms was broadly representative of the full sample of manufacturers

Thirty-six of our interviews were with senior executives or founders of 32 manufacturing companies. For 20 manufacturers of surgical masks and/or respirator end products, we learned details about when they first decided to enter the market, purchased machines, and began operation, as well as the markets they served and their external relationships.

Another 20 of our interviews were with government stakeholders (three federal regulators, one federal lab, two federal response coordinators, and six interviews at five states), industry associations, and other broader ecosystem players (nonprofits, etc.). To understand demand, as well as the institutional and industrial context, we also targeted state economic development organizations, regulators, consultants, and both MEP centers and Manufacturing USA institutes. The remainder of our interviews were with other entities in the mask and respirator manufacturing ecosystem that were responsible for regulating, supporting, or purchasing masks and respirators.

5. Results

In the results that follow, drawing upon our interviews, the timing of federal contracts, and broader trends in global PPE supply chains, we divide the pandemic into three key phases: phase 1 (intense supply shortages) between January and June of 2020, phase 2 (supply normalizing) between June and September of 2020, and phase 3 (imports resume) that begins September of 2020.[17]

5.1 Federal response: coordination with distributors, administration of the DPA, and federal contracts

The federal government response began in March of 2020 when military logistics experts were brought in to help the Department of Health and Human Services coordinate the pandemic response.[18] The federal government relied on close partnerships with major distributors to deliver PPE to "hotspot" counties experiencing COVID-19 outbreaks,[19] while also working closely with major US-headquartered mask and respirator manufacturers to match supply to identified

[17] Phase 1 refers to the most chaotic and uncertain period of the pandemic, where supply shortages were most acute, and demand was aggressive. Phase 2 refers to the following period, where global COVID-19 cases had fallen a bit, allowing countries and firms to catch up. Phase 3 refers to the period beginning September 2020, where imports (albeit slow imports) had begun to resume, and cheap Chinese masks and respirators were abundant in the market.

[18] Congressional Research Service (2020c); General Sanford Interview, September 16, 2021.

[19] The White House worked closely with the six major distributors of medical–surgical equipment to build out a system to observe granular deliveries of PPE to hospitals and attempt to match supply and demand (General Sanford Interview).

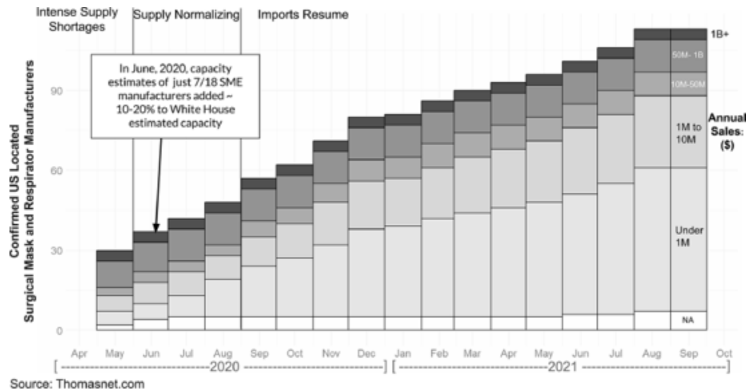

Figure 7. Manually validated surgical mask and respirator suppliers advertising on Thomsnet.com® over time. The firm size is based on D&B Hoovers. *Note:* Some firms are not on D&B Hoovers and thus have no size information, but we were able to categorize them as small, new entrant firms based on a manual review.

demand (hospitals, long-term care, first responders, non-health-care needs such as janitorial services, and laboratories and correctional facilities).[20] In total, between January of 2020 and August of 2021, federal agencies spent nearly $1.5 billion dollars on 7635 contracts for regulated masks and respirators, and other unspecified masks and respirators.

5.2 Domestic manufacturing response

Our results, based on real-time scraping of Thomasnet.com®, manual validation of firm locations and products through websites and phone calls, and D&B Hoover's information on firm size, show a rise in SMEs selling surgical masks, respirators, or their intermediary products (Figure 7).

Most of the manufacturers with under $10 Million in annual sales appeared on Thomasnet.com® only after September of 2020, after imports of inexpensive foreign products resumed. However, self-reported estimates of domestic manufacturing capacity of just seven SMEs from June 2020 add between 10% and 20% to White House estimates of domestic capacity from the top 5 major medical manufacturers in June 2020 (Polowyczyk, 2020).

5.3 Interview sample results: pathways, challenges, and bottlenecks to pivoting

5.3.1 Interviewed firm entry, federal support, and outcomes

As Figure 8 illustrates, two large firms in our interview sample were able to stand up new domestic plants, obtain regulatory approval, and serve massive, mainstream medical markets—in these cases within 3 weeks, and across multiple products—relying on their existing manufacturing and sourcing competencies in highly related products to do so (Honeywell, GM).

The remaining 18 smaller firms in our sample fall into three categories based on the period of the supply crisis during which they became operational: five SME firms became operational during the intense supply shortages, nine became operational while supply was normalizing, and four became operational once imports had already resumed.

Of the five SMEs that became operational during the early intense supply shortages (before June 2020), four of these firms drew on their existing distribution, manufacturing, and global supply chain competencies to operationalize quickly, while one new entrant (Firm Alpha) spent large sums (air freight for mask-making equipment, a consultant to accelerate the regulatory process, and extra workers to run a semi-automated line) to achieve speed. Of these companies, two sold to the medical market (HomTex and Firm Alpha), and they all managed to find high-volume nonmedical purchasers.

[20] In total, between January 2020 and August 2021, federal agencies spent nearly $1.5 billion dollars on 7635 contracts for regulated masks and respirators, and other unspecified masks and respirators.

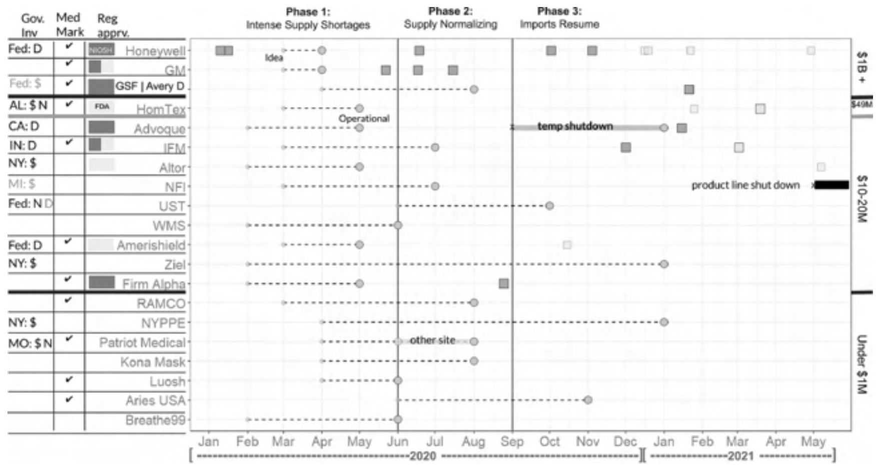

Figure 8. The timeline of interviewed firm activities. Each row represents a company. Firms are organized by D&B Hoovers' estimated 2021 annual sales. Moving to the right in each line, the first dot indicates when the firm had the idea to manufacture surgical masks and/or respirators (as identified in our interviews). The dotted line and the second dot represent the time until the firm began to produce masks or respirators off its manufacturing lines. The dark squares are dates of NIOSH approval. The light squares represent FDA approvals. The slightly smaller and lighter squares differentiate between FDA EUA approvals and full FDA 510K approvals. The Med. Mark column represents if the company sold to medical markets during the displayed timeline. The Gov. Inv. column captures any state or federal assistance, in direct money ($), network brokerage (N), or direct demand for products (D)

Of the nine firms that managed to become operational between June and September 2020, six new entrants became operational without any government support (one eventually receives augmenting support); one existing small company, Global Safety First (GSF) partnered with a large company (Avery Dennison) to produce their novel respirator product; and two melt-blown manufacturers, Indiana Face Mask (IFM) and National Filters Inc, stood up mask and respirator manufacturing lines with varying degrees of state support. Four firms (GSF, IFM, Luosh, and Patriot) sold to medical markets, with two of these firms (GSF and IFM) selling to medical markets through intermediaries. The companies that did not make it to medical markets found sales channels in food processing, utilities, prisons, and direct-to-consumer retail.

Four firms in our sample entered after September 2020. Aries was founded in the North Carolina Research Triangle and designed a mask with a novel filter material intended to satisfy new Occupational Safety and Health Administration workplace standards in response to the pandemic that were broadly anticipated, but ended up not being realized. The founders of UST recruited the engineer who stood up Honeywell's N95 facility in Arizona to enter into mask and respirator production. Ziel and NYPPE entered late because they needed to wait to receive NY state grant funds before purchasing machines. Respectively, it took seven and eight months for those funds to arrive. With the exception of Aries (which managed to sell to hospitals, clinics, universities, and manufacturers), these firms struggled to find sales channels and get regulatory approval but donated goods to hospitals and the local community.

5.3.2 Common successes, challenges, and bottlenecks to entry

Many of the SMEs in our sample experienced similar challenges. These challenges included accessing information (especially trusted equipment suppliers), regulatory barriers (in terms of time and cost of certification, and especially for commercializing novel products), breaking into mainstream hospital markets, and accessing capital to finance a factory and stand up a production line.

Companies had difficulty accessing information on how to make medical-grade masks and faced major hurdles in access to machines, including quality issues, shipping delays or costs, lack of assembly and run knowledge, and shortages in maintenance supplies. While some used air freight to expedite the process, the delivery of machines (from China) was slowed by cargo shipping delays. When the machines arrived, they were in pieces and required creative engineering and problem-solving to operationalize. To quote Luosh: "you get these machines, there's no instruction manual, there's no documentation […] on top of that, the control systems were in Mandarin."[21]

Qualification and certification costs and delays created additional barriers for many companies, with companies struggling in getting NIOSH, FDA EUA, and/or FDA510K approval. For example, Patriot Medical applied for the surgical mask EUA early in the pandemic, but never heard back. They prepared materials to submit for FDA 510K approval, but by then, requirements had changed, and the new cost of $100,000 was too much.[22] Four of the interviewed firms mentioned specifically hiring regulatory consultants to navigate this process, but had highly heterogeneous experiences, with only some consultants helping accelerate regulatory approval (as in the case of Firm Alpha). Furthermore, companies encountered significant difficulties in commercializing and certifying novel products (Aries, GSF, and Breathe99).[23]

The most pervasive challenge faced by the SME firms in our sample was in gaining access to hospital purchasing systems. In describing the experience of trying to sell to hospitals, one company said: "[the hospital] world doesn't care about country of origin, it only cares about price and [familiarity], and they buy name brands that have [familiarity] and cheap products."[24] Firms also struggled to list products on retail sites such as Amazon, Etsy, and Google. One company described their experience in trying to list on Amazon as playing whack-a-mole, where once they got through the vetting process to be listed as a surgical mask, they would find themselves suddenly removed due to an automated system and have to restart a long process of speaking with non-supportive customer service representatives over again.[25]

While some SME firms in our sample were able to gain access to the medical market (at least temporarily), many benefited from finding volume sales avenues outside of mainstream hospitals, such as small hospitals, dental clinics, construction and manufacturing site workers, and directly to consumers.

The firms that became operational by September 2020 also had certain common themes in describing their successes. In terms of human capital, our sample companies benefited from persistent founders and technically skilled "MacGyvers", as well as the unexpected discovery of high-performing operators. One former Boeing aerospace engineer got his machine operational in 3 days; one company described an employee who was a former grocery deli chef who became a top machine operator[26]; while another company described how female employees (even those without previous manufacturing or machinery experience) consistently proved to be especially high-performing operators.[27] Companies also found success in leveraging networks, sometimes through corporate partnerships or industrial associations, and sometimes through federal government or state help. To quote one company: "[our founder] is a master networker so […] it's not hard for him to pick up a phone and go sit down with somebody."[28]

Most of the companies we spoke with were able to overcome shortages in the intermediate materials they needed, including obtaining latex-free elastic and melt-blown filter material, through networks or persistence. In the case of melt-blown filter material, the federal government also invested in increasing the overall domestic supply.

5.4 State government support of firm entry/expansion

In contrast to the federal government's "all-of-government" response to the pandemic—which sought to coordinate across HHS, DOD, FDA, and other agencies—state governments were highly

[21] Luosh Interview, January 26, 2021.
[22] Patriot Medical Interview, April 20, 2021.
[23] In both of these latter cases, the lack of a previously certified, effectively similar predicate device created challenges for regulatory approval.
[24] Advoque Interview, March 16, 2021.
[25] Wisconsin Medical Supply Interview, January 21, 2021.
[26] Luosh Interview, January 26, 2021.
[27] Ziel Interview, January 25, 2021.
[28] Surgical Mask Manufacturer Interview, January 23, 2021.

varied in the extent to which they managed to coordinate across agencies (e.g., state-level department of commerce and department of health), as well as across regions. For example Alabama ran operations through the state department of commerce, worked closely with the state department of health and public hospitals to connect manufacturers to end users, and used regional economic development actors and universities to identify and interface with local manufacturers. Conversely, North Carolina, the emergency management services established a cross-organizational governmental operation early in the pandemic, but this operation was short-lived. Similarly, a state of Washington department of commerce official described some difficulties in coordinating with the state department of health. In New York, each of the five regions pursued an independent approach, without an explicit state-driven plan.

In our sample, our interviewees and firm results reflect positively on state governments that had knowledge about firm capabilities and acted to augment firm investments, either through brokerage services (especially to connect firms to the medical market or navigate regulatory processes), or through the provision of capital. Examples of brokering include Alabama, which worked closely with manufacturers (that they already had relationships with) and the Department of Public Health; New York City, which modified procurement policies to allow SME firms to partner together and serve larger contracts; Indiana, which partnered closely with specific firms and acted as a distributor; and North Carolina, which helped firms navigate testing and regulatory processes (relying on a rich textile ecosystem to provide other services to firms). Examples of effective distribution of capital include state assistance helping firms expand product lines in Alabama, Missouri, and for Altor Safety in New York. Our research suggests firms did less well, especially in terms of speed, when they were reliant on state-provided capital to start production (such as in the case of Ziel and NYPEE in New York, where firms were delayed multiple months while waiting for funds to come through) and when asked by the state to enter the mask and respirator market (such as in the case of Indiana and Michigan). However, it is unclear the degree to which higher-quality state support would have improved outcomes for these firms, or if these firms were less qualified or less-willing contributors.

6. Discussion: short-term economic dynamism as a policy tool during crises

6.1 Large-firm entry advantages in speed, scale, and government assistance

The needs for significant firm competencies in the rapid sourcing, manufacturing, and distribution of large volumes of regulated, safety-critical products, combined with hospital preferences for trusted providers that could deliver multiple products together, favored entry and scale-up by large multi-business (Lieberman *et al.*, 2017) and multiproduct (Bernard *et al.*, 2010) firms during the pandemic. These large firms were able to leverage joint ventures (Kogut, 1991) and existing organizational experience (Agarwal and Gort, 2002; Costa *et al.*, 2023). The successes (in terms of speed, scale, and regulatory approval) we observe for large firms entering into the production of a mature product during a global crisis are consistent with the existing literature on the advantages large firms have during entry into the mature phase of a product life-cycle (Gort and Klepper, 1982), and for operating flexibility in global manufacturing environments (Kogut and Kulatilaka, 1994; Graves and Tomlin, 2003).

Unfortunately, given the scale and scope of the global pandemic, the response by large, established manufacturers was insufficient to adequately meet hospital demand, let alone broad commercial and consumer demand in the workplace, at schools and homes, and in other non-medical settings. Missing from both the federal government's playbook, as well as the existing literature, is an understanding of the role that SMEs might (and did) play in alleviating shortages, as well as the unique challenges that they face and how policy at different levels (Flanagan *et al.*, 2011) can address these challenges.

6.2 The opportunity presented by SMEs and cases of network failure

In response to unfulfilled demand during COVID-19, an impressive variety of timely and successful SMEs[29] entered into the production of medical-grade masks and/or respirators. These entering SMEs faced challenges, including information asymmetries and overcoming regulatory, capital, and market entry barriers,[30] as consistent with existing literature on entry barriers to new competition (Bain, 1956; Caves and Porter, 1977; Whitford, 2005).[31] While individual SMEs often lacked the entire suite of capabilities necessary to both operationalize manufacturing and break into and contribute to traditional markets, our results suggest that the most successful ones leveraged network partnerships with both small and large companies, and sometimes public entities, to successfully break into high-volume markets and bring new products to the market. This rare persistence of firm performance (Dosi *et al.*, 2020) and leveraging of external networks to fill competency gaps potentially being a precursor of success are consistent with the existing literature on how SMEs can leverage prior founder experience, knowledge, and networks to facilitate entry, increase survival, and mediate the impact of size (Agarwal *et al.*, 2002; Klepper, 2002; Dencker *et al.*, 2009; Sosa, 2012). It also speaks to the characteristics that may be necessary for a successful role for government in facilitating entry to support *short-term economic dynamism* during crises.

6.3 State and federal roles in supporting short-term economic dynamism

Our findings suggest situations in which federal *versus* state roles may have a comparative advantage (Romano, 2006; Morgan, 2017; Singerman, 2020). Furthermore, the heterogeneity in state responses (Hale *et al.*, 2020) offers unique insights into some of what is needed in effective state ecosystems.

Here, our research suggests that the federal government can play a facilitating and brokerage role by acting as a repository of central information, reducing entry barriers including access to early funding, engaging in regulatory adaptability and lowering certification costs (Roca *et al.*, 2017; Piore and Schrank, 2018; Johnson *et al.*, 2022), brokering connections to commercial and noncommercial markets (such as through connecting firms to large distributors), and guaranteeing a market (such as through mandates, advanced market commitments (Kremer *et al.*, 2020), or programs such as the proposes US postal service plan to send five surgical masks to every American household). The federal government may also have a role in providing certain foundational services to *states*, especially in providing funding (e.g., NIST MEP), and disseminating best practices across states.

Our results build upon Reynolds et al. (2021)'s Massachusetts-based pandemic findings, suggesting the importance of cross-organizational and cross-firm investments in manufacturing ecosystems pre-crisis, to highlight the importance of *government* transactive memory (Argote and Ren, 2012) in two functions—brokering of partnerships and the provision of capital—to support *short-term economic dynamism* during crises. The noncrisis literature on manufacturer upgrading describes how state-funded intermediaries can help broker relationships between manufacturers and knowledgeable public and private entities to provide complementary capabilities (MacDuffie and Helper, 1997; Whitford and Zeitlin, 2004; McEvily and Marcus, 2005; Helper and Stanley, 2007; Schrank and Whitford, 2011; Whitford and Schrank, 2011; Brandt and Whitford, 2017; Brandt *et al.*, 2018), brokering among large manufacturers, their suppliers, and other regional actors (Feldman and Zoller, 2012; Whitford, 2012). Our results suggest that during

[29] Diversifying SMEs and *de novo* firms (hereafter all referred to as SMEs).

[30] In the case of respirators, there are additional market entry barriers beyond those suggested by Whitford, in that there are direct monetary disincentives for hospital purchasers to use nonincumbent products, especially from SME firms, including per-unit certification costs and hospital system preferences for high-volume, multi-product packages.

[31] Despite these entry barriers, our results suggest that SMEs played a role in filling gaps between supply and demand, especially for markets not served by major medical manufacturers and distributors, such as smaller medical clinics, nonmedical purchasers (e.g., construction, utilities, manufacturers, and schools), and consumers. These results match Whitford (2005), who finds even in noncrisis situations that SMEs in certain cases ramp-up capabilities but struggle to gain entry into mainstream markets that have existing supplier relationships and networks.

crisis-induced shortages, particularly important is being able to leverage pre-existing knowledge of regional actors (both public and private entities) to coordinate not only within industries and across production networks (as the current literature emphasizes) but also between manufacturers (especially SMEs newly entering the product space) and existing distributors and legacy purchasers (such as hospital systems). Whereas noncrisis literature finds an important role for state start-up capital in supplementing federal investments (Lanahan and Feldman, 2018; Zhao and Ziedonis, 2020), our results suggest during crises preexisting state knowledge of regional actors and their capabilities may be as or more important in allocating capital. Indeed, we find that to quickly respond to sudden life-threatening shortages, state capital might be most effective when it augments investments firms have already made, rather than providing start-up capital for firms (e.g., expanding existing product lines as opposed to establishing a first product line).

As summarized in Figure 9, the respective strengths of the federal and state governments may be able to be leveraged complementarily during crises: where the federal government serves as both a central repository for information and broker to large distributors, while state governments augment the existing efforts of SMEs and coordinate local linkages and partnerships. Indeed, past research suggests that this support may be most effective when coordinated through regional centers that focus on regionally specific brokerage activities (Brandt *et al.*, 2018) that pair SME firms with other entities that can complement their competitive capabilities (McEvily and Marcus, 2005), including governmental entities, other firms, and nongovernment actors such as philanthropies and universities.

Based on our cases across states, we propose that for brokering and provision of capital to be effective, it is particularly important that intermediaries have transactive memory a system for individuals, groups, and organizations to store and retreive knowledge across domai or insider knowledge of individual firms (Argote and Ren, 2012) and the ability to identify and facilitate connections to fill gaps in firm capabilities. Such state brokering assistance can include gaining access to mainstream markets (Kremer *et al.*, 2020), ensuring the supply of material and human capital, and providing services to support firms in navigating the regulatory process (Roca *et al.*, 2017). In the case of providing capital, this insider knowledge is important to know if firms are well positioned or already entering on their own (Schreyogg and Kliesch-Eberl, 2007). Learning from the heterogeneity across state responses, we hypothesize that this preexisting transactive memory (Wezel *et al.*, 2006; Teece, 2007; Bapuji *et al.*, 2012; Turner and Fern, 2012), across the suite of actors involved in a regional ecosystem (from private firms to NGO external actors, universities, and public institutions), is particularly important during crises, especially concerning the speed and scale of the response. Here, the state level is sufficiently local to have active knowledge, while sufficiently central to support coordination and avoid confusion across actors in a situation requiring a speedy and timely response.

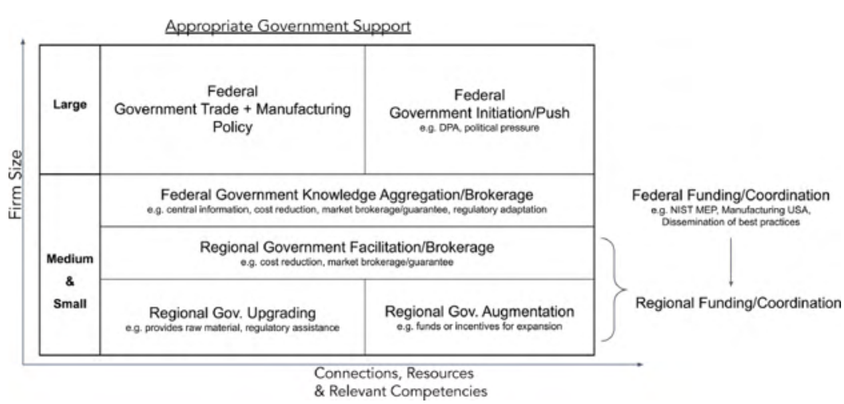

Figure 9. Hypothesized roles for state (regional) and federal assistance in supporting firm entry, for firms of different sizes, with different degrees of connections, resources, and relevant competencies (left)

6.4 When are markets enough? The implications of the nature of the crises for government roles in supporting short-term economic dynamism

While the federal government helped direct and support the industrial response to the pandemic (especially in vaccines and allocating PPE to hotspot areas), our findings support the theory (Herrigel, 2010) that a significant amount of the industrial response and recomposition was industrial actors independently reallocating and assembling resources and entering into new product spaces in response to crisis-induced demand spikes and new supply chain constraints. Indeed, although market response without government intervention was timely (3 weeks) and high volume, it was just insufficient to meet the domestic shortage.[32] Overall, the limited ability for the market to act quickly on its own (and thus the need for government intervention during sudden crises) to ensure public well-being during global shortages in life-preserving products will depend on the scale of the shortage, the size and intensity of entry barriers (e.g., technical, market, and regulatory) of the products with shortages, the need for speed, and the implications of failure to respond for public well-being (here, loss of life).

Our results augment the current mainstream National Response Framework (National Response Framework, 2019; Organisation for Economic Co-operation and Development [OECD] Toolkit for Risk Governance (n.d.)) by adding the role of *short-term economic dynamism* and nuancing the potential role for state versus federal action. As with pre-pandemic practices, when shocks induce shortages for products central to social welfare (here human lives), and the scale of shortages is not met by the market response, the most rapid and effective option is for the federal government to approach existing, large firms with relevant domestic capabilities to scale-up production capacity ("government initiation/push"). If this production capacity, however, is still insufficient, state governments can provide augmenting support (in the form of additional capital) to well-connected, resourced, and competent firms attempting to respond to the crisis. Where actions of these connected, competency-rich small firms are still insufficient to meet crisis-induced demand, state government assistance might be able to support less-resourced SMEs in upgrading their capabilities, by providing both brokering and capital. Given the greater preparedness of other firms in the system, such *during crisis* government upgrading should only be done when there is such a severe shortage of critical products (as was the case in the global pandemic) such that the capability of more resourced firms is insufficient.

6.5 Lessons for the future

The COVID-19 pandemic offers a unique opportunity to observe manufacturers' decisions and ability to pivot in response to a global spike in demand, in this case for mask and respirator production. In working to draw more general insights, it is important to consider the specific market, product, and technology context of surgical mask and respirator manufacturing during COVID-19, and where dimensions may or may not generalize to other contexts.

The implications about generalizability that stem from the unique dimensions of the mask and respirator manufacturing response to the COVID-19 pandemic are described in Table 2, where mask and respirator manufacturing is of relatively low technological and product complexity, is an industry dominated by large distributors and long-standing supplier relationships, is safety-regulated, and has per-unit certification costs. In addition, masks and respirators are also relatively simple commodity products with low product differentiation and high-price elasticity (particularly for hospital buyers). While under non-pandemic circumstances producing a commodity product in a region with high-factor inputs could have been prohibitive, during the most intense periods of global and local shortages, both medical and nonmedical markets were searching for reliable replacement suppliers for medical products and were also willing to pay much higher prices to gain access to health-critical supplies.[33] From a sales perspective, the high-price elasticity of large buyers further complicated the task of breaking into large medical markets,

[32] Importantly, the shortage was in the case of COVID-19 global (in contrast to, for example, Ebola, where the shortage was local, or H1N1), and national actors were intervening in market flows for domestic and geopolitical advantage.

[33] The price of respirators increased from less than $1 per unit to $12 per unit, with an average of between $4 per unit and $5 per unit in July 2020 (USITC, 2020).

Table 2. Dimensions elucidated by mask and respirator manufacturing response to the COVID-19 pandemic

Dimension	Similar	Different	Implication	Proposed government role
Low technological and product complexity	Needles, glass vials, gloves, tires	Ventilators, semiconductors, batteries	Low barriers to entry for production, particularly for SMEs	Some information asymmetries that the government could support relieving to accelerate entry
Dominated by large distributors and long-standing supplier relationships	Defense, pharmaceuticals, medical devices	Direct-to-consumer retail, software, and video games	High barrier to entry for sales, particularly for SMEs; may produce but fail to sell to large distributors	Validation—certifications of quality; broker—increase connections to large distributors; government serves as a distributor—contracting mechanisms that allow SME companies to bid on a large contract as a group
Safety- regulated	Medical, aviation, transportation, workplace, and occupational safety	Software, retail products	Higher barrier to entry for sales, particularly for SMEs or companies without prior regulatory experience	Subsidize certification costs; facilitate accelerated training; adapt or modify without sacrificing safety; prioritization of applications from domestic manufacturers during crisis (higher probability of quality, access)
Per-unit certification costs	Custom medical equipment or treatments, custom safety equipment, customized machinery	Semiconductors, pharmaceutical drugs	Higher barrier to entry for sales, particularly for new products	Subsidize distribution of free initial product for per-unit fit testing, cost of per-unit fit testing, and provision of additional fit testing workers (and associated fit testing training); spur innovation to reduce per-person fit testing time, ease, and costs

especially once imports resumed after August 2020. However, in the initial days of the pandemic, there were many incentives for firms to manufacture masks and respirators, especially with the high volume of calls and requests for urgent aid.

We hypothesize that each of these dimensions influenced the presence or absence of entry barriers that would-be mask and respirator manufacturers face. The applicability of the results of our research to other industries and products might be mitigated by the intensity of entry barriers that companies may face. Across each of the product and market dimensions, appropriate government action could have reduced entry barriers and might do so for similar situations in the future.

In the relatively low-entry barrier case of surgical mask and respirator manufacturing, government action could have further reduced entry barriers. Provision of publicly available information on product designs and trusted equipment and material vendors might have accelerated production timelines. The entry barriers imposed by large distributors could be circumvented by modifying procurement systems to help smaller suppliers form groups (as was done in New York City), having the government act as a broker between new SME entrants and large hospital networks (as was done in Alabama), or having the government act as a distributor (as was done in Indiana). While important, the regulation process could be adapted or modified without sacrificing safety (Bonin-Roca *et al.*, 2017)—such as through prioritization of applications from domestic manufacturers and closer communication with domestic manufacturers, as NIOSH reportedly engaged in.[34] Payment or waving of per-user certification costs could be subsidized by the government, where the government could include free distribution of a sample of masks for fit testing along with regulatory approval and with more investments at the regulatory agency level to spur innovation to reduce per-unit certification costs.

Clearly, identification of the appropriate type and form of government intervention requires an understanding of the different dynamics facing large and small firms in redeploying resources and entering into new product spaces.

7. Conclusions and potential policy implications

The COVID-19 pandemic forced a short-term reorganization in global production, with firms changing both their product line and production location in response to an intense surge in global demand, supply chain bottlenecks, and global shortages. During this period, the federal government relied heavily on large multinational manufacturers to address surgical mask and respirator supply shortages. While these companies excelled at rapidly redeploying resources across both product lines and geographies to meet the need, they were insufficient to meet all existing demand, especially demand not fulfilled by large hospital distributors. Missing from the government playbook was the role that *short-term economic dynamism* (firm entry and expansion by diversifying and *de novo* firms) could play in alleviating shortages.

Our results suggest that some SMEs were impressively fast in standing up new production lines, but faced challenges. The speed and scale of response by these SMEs would likely have benefited from improved data, and support, such as through a single location portal for high-quality public information (e.g., Yale's SalivaDirect) on trusted equipment suppliers and product specs, as well as the cultivation of a community of shared practice around ramp-up lessons learned. We propose a new theory for how federal and state governments might better support *short-term economic dynamism* to respond to crisis-induced shortages, especially for SMEs. Here, federal leadership might have been able to address some of the bottlenecks faced by SMEs, especially in terms of more transparent regulatory adaptation, reduction in certification costs, and FDA labor ramp-up in response to a rise in applications. Supply might also have benefited from increased access to federal or state contracts for entry and through greater assurance of market demand (such as Germany's N95 mandates). The state economic development ecosystems we studied differed

[34] One of the insights of our research is that while the United States passed simpler (and often more extensive) EUAs than most OECD countries did (Amaral *et al.*, 2023), access to these EUAs was uneven between large and SME firms. While large firms were able to take advantage of EUAs to quickly obtain regulatory approval, SME firms struggled to do the same.

substantially in their ability to support and cultivate their manufacturing ecosystems during the crisis, with some demonstrating a higher degree of access to and awareness of regional SME manufacturers' capabilities and others struggling to provide knowledge, connections, or funds in a timely fashion. This high degree of heterogeneity in state dynamic coordination capacity suggests that the federal government may also have a role in supporting manufacturing ecosystems through the identification and cultivation of state and local best practices, agencies such as the Economic Development Administartion and Small Business Administration, and institutions such as the Manufacturing USA institutes and NIST MEP centers.

Future research is needed to understand the most effective policies to develop state-level preexisting knowledge and relationships with firms of different sizes pre-crisis to facilitate short-term economic dynamism, as well as what (if any) policy support following crises is necessary to facilitate firm transitions into new product spaces as they exit product spaces no longer experiencing shortages.

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National core competencies and dynamic capabilities in times of crisis: Adaptive regulation of new entrants in advanced technology markets

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A B S T R A C T

The extent to which domestic industrial capabilities are essential in contributing to a Nations' prosperity and national well-being is the topic of long-standing debate. On the one hand, globalization and the outsourcing of production can lead to greater productivity, lower product costs, and gains from trade. On the other hand, national capabilities have long been a source of competitiveness and security during times of war and other crises. We explore the importance of domestic industrial capabilities during crises through a comparative case study of two countries - Spain and Portugal - to the sudden spike in demand for the manufacture of mechanical ventilators brought on by the COVID-19 pandemic. Both countries had to work within the framework of EU regulations, but had very different internal competencies upon which to draw in doing so. In addition, mechanical ventilators serve as a particularly interesting context for study because they involve high risk (loss of patients' lives if incorrectly manufactured) and entering the market presents high entry barriers (including significant tacit knowledge in its production and use, and significant intellectual property embedded in proprietary software at large, established firms). To unpack the processes used by each country we leverage insights from 60 semi-structured interviews across experts from industry, healthcare workers, regulators, non-profit organizations, and research centers. We find that Spanish regulatory measures were more effective, resulting in 12 times more new products receiving regulatory approval to enter the market. Although neither country is known for their mechanical ventilator production, instrumental in informing the Spanish regulatory and industrial responses was their internal knowledge base due to domestic experts and existing capabilities in ventilator production. We conclude by proposing new theory for how nations might identify important core competencies to enhance their dynamic (regulatory) capabilities in areas likely to be critical to their social welfare.

1. Introduction

The extent to which domestic industrial capabilities define nations' prosperity and success is a topic of long-standing debate in academic and policy circles (Nelson, 1993). On the one hand, globalization (Krugman, 1999; Samuelson, 2004) and production outsourcing (Vernon, 1966; Bhagwati et al., 2004; Acemoglu et al., 2012) can lead to greater productivity, lower product costs, and gains from trade. In this context, scholars have documented the productive advantages that certain countries achieve by focusing on a service economy (Walker, 2004; Buera and Kaboski, 2009) (rather than manufacturing) and as well as the global distribution of labor in R&D (Branstetter et al., 2015). On the other hand, the existence of domestic production has also been identified as a necessary condition to create spillovers to the host country through inter-firm linkages (Zysman et al., 1997) and industry commons (Pisano and Shih, 2009), and manufacturing is known to have disproportionate outcomes in terms of R&D spending and high-wage high-school educated labor (Helper et al., 2012), as well as positive spillovers for innovation (Fuchs and Kirchain, 2010; Fuchs, 2014; Autor et al., 2017; Branstetter et al., 2017).

Separate from debates about these issues under steady-state conditions, national capabilities have long been seen as a source of competitiveness and security during times of war and other crises (Hounshell, 1984; Zeitlin, 1995; Zachary, 1999; Herman, 2012). Indeed, past literature suggests that the location and ownership of firms contribute to the nation's competitive advantage (Porter, 1990; Pitelis and Teece, 2016), especially when considering their resources (Wernerfelt, 1984; Barney, 1991), core competencies (Prahalad, 1993; Coombs, 1996), and

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dynamic capabilities (Teece et al., 1997; Pisano, 2017). While some literature has tried to understand how to create more flexible and adaptive regulation (Bonnín Roca et al., 2017; Piore and Schrank, 2018) there has been a lack of empirical evidence on how to build dynamic national capabilities, including in technologically complex manufactured products critical for security or welfare. The COVID-19 pandemic provides the opportunity to study this issue, which has relevance in a wide variety of crises and black swan events.

Our paper focuses on the worldwide shortage of mechanical ventilators caused by the COVID-19 virus (GlobalData, 2020) and the role that national domestic competencies played in shaping countries' regulatory responses and the emergence of new entrants. Mechanical ventilators are particularly challenging to manufacture as they are technologically complex and require significant tacit knowledge, both during their production and when used with patients. The asymmetrical global production of such medical devices (eight companies serve 80 % of the world market (Staff, 2020)) makes asymmetries in access during a global crisis even more likely. Further, without a domestic manufacturer of such products, most countries lack relevant internal regulatory bodies and the competencies needed for ventilator manufacturer and regulation. While under day-to-day circumstances these two internal competencies might not be paramount, in a health crisis such as the COVID-19 epidemic, these capabilities may be critical in defining a nation's ability to protect its national interest in public health. Addressing this issue is important in its own right, but also because there are reasons to think that similar crises may become more common in the future (Hilsenrath, 2020).

Our paper builds new theory on dynamic national capabilities through a comparative case study of how two European countries (Portugal and Spain) adapted European regulations to facilitate new ventilator manufacturer entrants during the COVID-19 pandemic. We conducted 60 interviews (32 in Portugal, 24 in Spain, and 4 with the European regulatory bodies), triangulating insights shared by new entrants, incumbent firms and their associations, and national and international regulatory bodies in each country.

We find that Spanish regulatory measures were more effective, resulting in 12 times more new products entering the market. Meanwhile, Portugal kept existing pre-COVID regulatory requirements unchanged, and only managed to approve one new ventilator manufacturer after seven months when cases had already begun to decline. Although neither country is known for their mechanical ventilator production, instrumental in informing the Spanish regulatory and industrial responses was their internal knowledge base due to domestic experts and existing capabilities in ventilator production.

We demonstrate for the first time the importance of domestic manufacturing for dynamic regulatory capabilities during times of crisis. Our results suggest that it is the *existence* of manufacturing, and the tacit knowledge that goes with it, rather than the size or capacity of those manufacturers, that facilitates rapid adaptation of regulation. Countries with domestic manufacturing of such products prior to a crisis have experience regulating those products, as well as industry stakeholder knowledge that can be brought to bear in adapting that regulation to facilitate safely expanding production by supporting new entrants during a crisis. Countries should consider this additional dynamic regulatory advantage when assessing the value of investing in the domestic manufacturing of critical products. Because it is expensive to maintain manufacturing in several different sectors, countries unable to afford domestic manufacturing may benefit from establishing pre-crisis partnerships with countries that have such capabilities – not just to potentially locate manufacturing in-country during a sudden demand spike but equally to share knowledge and expertise to adapt regulation to safely support new local entrants. The European Union would be well-served to act now to get its countries with domestic manufacturing to pre-agree to share knowledge to support the safe and adaptive regulation of new domestic manufacturers of safety-critical technologically complex products during crises when global shortages mean they cannot share the product itself.

2. Theoretical background

2.1. National innovation systems, core competencies, and dynamic capabilities

A variety of scholars have sought to understand the domestic ingredients to support national competitiveness. Johnson in 1982 (Johnson, 1982), highlights the importance of the developmental government role in industrial or technology development, in the context of a singular culture, through elite bureaucrats in central agencies and institutions. In his comparative study of 15 countries including large market-oriented industrializing nations, smaller high-income countries, and newly industrialized states, Nelson (Nelson, 1993) concludes that the only clear predictors of innovative performance are a nation's education and training; having fiscal and monetary and trade policies that compel national firms to compete on the world market; and in manufacturing having technological efforts by firms (beyond those by governments or universities). Nelson also suggests that countries with large affluent populations can more easily provide protected markets for a wide range of manufacturing industries, and that small high-income countries must either have rich natural resources (whether oil and minerals or for farming) or focus on export-oriented manufacturing and an innovation system that supports this (Nelson, 1993). Similarly, Breznitz (Breznitz, 2007) shows empirically that the rise of globalization has given new economic development opportunities for emerging economies than ever before, especially in the case of innovation-based industries where technology has become the final product and its production is increasingly fragmented around the globe. In his study, Breznitz challenges old and neodevelopmental-state theories by highlighting the differences between state structures and state-industry relationships that lead to disparate state choices which, in turn, directly influence the development of distinct national capabilities. While Acemoglu and Robinson (Acemoglu and Robinson, 2012) agree on the importance of education and export-oriented innovation systems, they focus on the significance of inclusive institutions (e.g. unbiased system of law, securing private property, upholding contracts, encouraging new business) for Nations' prosperity and Citizen's welfare, over geography or culture. Whilst all these theories seek to explain a nation's competitiveness, they lack the ability to predict which countries are expected to perform best during a crisis.

A separate literature has focused on the drivers of firm's abilities to sustain competitive advantage, and in including the importance of (critical) resources (Wernerfelt, 1989; Peteraf, 1993) or core competencies (Prahalad, 1993; Coombs, 1996; Mascarenhas et al., 1998) and the implications of different configurations of these competencies for competitiveness (Barney, 1991; Sidney G. Winter, 2003). In this literature, a group of scholars has focused on how firms' dynamic capabilities not only can provide momentary competitive advantage but also sustain it (Teece et al., 1997; Eisenhardt and Martin, 2000; Helfat and Peteraf, 2009; Pisano, 2017). These dynamic capabilities, which emerge from path-dependent processes (Nelson and Winter, 1982), involve a firm's organizational routines (Winter, 2000) that enable it to continuously recombine its existing resources (Reed and Defillippi, 1990), develop new ones (Zollo and Winter, 2002), and match (Teece, 2010) those capabilities to the challenges posed by outside competitors and markets. Research to date has largely failed to explore if theories of core competencies and dynamic capabilities of the firm have relevance in the context of nations. While the ideology of techno-nationalism argues that the ownership and location of firms (and their resources, core competencies, and dynamic capabilities) contribute to national competitiveness (Nelson, 1993), little research to date has studied this linkage empirically, and indeed, research on the country-less-ness of multinational corporations might suggest the opposite (Fransman, 1997).

2.2. Adaptive national responses during crises

During a crisis, a wide range of context-specific entry barriers can prevent firms from penetrating new markets including supplier dependency (Caves and Porter, 1977; Karakaya, 2002), access to tangible and intangible resources (Acs and Audretsch, 1989; Agarwal and Gort, 1996), market competitiveness (Bain, 1956; Levin, 1978), and regulation (Geroski, 1995; Mcafee et al., 2004; Fattal-Jaef, 2019). Here, policies and regulations are unique in that they offer nations an opportunity to directly impact market dynamics (Belenzon et al., 2019). Examples of regulations that directly influence entry are anti-trust regulation (Demsetz, 1982; Schmalensee, 2004), tax advantages (Bond and Samuelson, 1986; Desai et al., 2002), or state investment and subsidies (Haaparanta, 1996; Blomström, 2002). Also, importantly, the adaptiveness of regulation is independent of the market entry barriers that regulation may create - regulation could adapt to create lower or higher entry barriers (Eichler et al., 2012).

Major regulatory changes frequently happen after a crisis (Temin, 1985; Baumgartner and Jones, 2010) due, among other things, to the gap between the bureaucratic procedures set in place before a crisis and the emergent norms (Schneider, 1992). Rapid changes in regulation have also been implemented during crises to tackle difficult problems in previous crises and, in the case of the swine flu, it was found that different entities implemented different regulations (Versluis et al., 2019). In a wide range of settings scholars have noted the limitations of making changes to established regulation during or after crises and have explored how to more proactively create flexible regulation (McCray et al., 2010; Eichler et al., 2012; Bonnín Roca et al., 2017) so as to better address: on-the-ground realities (Piore and Schrank, 2018); adapt to changing environments (e.g. technology change, change in industry structure, sudden shocks such as would occur during crises): and, prevent regulatory lock-ins, i.e., regulations that lock in inappropriate features or ignore key issues (Wilson et al., 2007). Mechanisms include, for example, the periodic revision or use of sunset dates at which the regulatory needs and actions should be reassessed (Wilson et al., 2008; Sunstein, 2013).

A wide range of countries rely on international or other national regulatory bodies to guarantee the conformity of the products to be introduced in their domestic markets (e.g. Bolivia, Colombia, in Medtech). While this has proven useful for such countries, in the event of a crisis national regulatory bodies do not necessarily need to provide international support or guidance. One way the EU proactively permits changes during crises is through the creation of articles or clauses that allow EU member-states to act on their own (in the case of medical devices, see article 59 MDR (The European Commission, 2017)). While day-to-day regulations are developed and overviewed by EU regulatory bodies, in these "temporary opt-out" articles each nation needs to devise its own strategy and emergency policies. In this context, not every country may have the necessary institutions, and competencies in place to deal with such problems. Absent from the literature has been a discussion of which national competencies are necessary to deal with crises that require sudden changes in regulation, and how these competencies may vary depending on the knowledge intensity and safety-criticality of products.

3. Industry and regulatory background

3.1. European regulatory context

Until the 1990s, there was no European common regulation of medical devices. Each member-state had its own regulatory system. The first proposal to unify Europe's uneven and complex medical market was the establishment of the Conformité Européenne (CE), which identified the regulations with which medical devices had to comply in order enter the European market (Kramer et al., 2012). Until then, most manufacturers enjoyed such good relations with health administrators that, in many countries, the manufacturers had monopoly status (Altenstetter, 2003). The highly regulated mechanical ventilator market has followed this tendency of manufacturers having monopoly status in individual countries. Only a handful of enterprises scattered around the world hold the majority (80 %) of the world's production volume (Staff, 2020).

The CE's first proposal was in fact a directive, not a regulation. Proposed in 1993, The Medical Devices Directive (MDD) (The European Commission, 1993) affected three key stakeholders: Medical Devices Manufacturers, Notified bodies, and Competent Authorities. Notified Bodies (henceforth, NB) are certification organizations designated by the EU countries that certify products to be able to be sold under the CE within the EU. The NBs assess the conformity of products to EU requirements, including medical devices, and also inspect manufacturing sites (Kramer et al., 2012). NBs are primarily private organizations that work in the interest of the public on a fee-based contractual basis (Altenstetter, 2003). That said, some European countries have their own public NB. Either private or public, these NBs are designated by each Member State (The European Commission, 2017) and each Member State's Competent Authority is responsible to ensure the NB's independence, professional integrity, and impartiality (The European Commission, 2017). Due to the international nature of the European regulatory framework, not every country needs to have an NB. As of early 2021, some countries such as Portugal, Estonia, or Austria had no NBs, Spain had one NB, while countries like Germany – with a strong medical technology industry, had 10 Medical Device NBs (The European Commission, 2021). One interesting nuance of the established regulation is that, regardless of the manufacturer's country of origin (within or outside Europe), the manufacturer of the medical devices can choose any approved NB to certify its products.

In both MDR and MDD, medical devices are classified into three different classes, according to risk levels, ranging from Class I (lowest risk) to Class III (highest risk) (The European Commission, 1993, 2017). Mechanical ventilators are life-supporting medical devices. Their degree of risk is, according to the MDR (The European Commission, 2017) classified as class 2a or 2b. The approval process for class 2a and 2b medical devices, as illustrated in Fig. 1, consists of five steps (3 + 2). The first three steps have to be followed only one time per product and, once it is finalized, the product is certified according to the EU regulation. The final two steps address the marketing of the product in different European markets. Once the product is certified, the manufacturer has to notify the competent authority from each country to enter the product in that market. The Competent Authority is then responsible to oversee the performance of the product in that specific national market. All these steps require that the manufacturer is the producer of a medical device that follows the Quality Management System (QMS).

To understand the hurdles facing new products and new entrants in medical markets during normal times, and how they subsequently were adapted during crises, it is important to understand each of the five steps in the EU approval process in detail: The first step consists of the preclinical studies of a medical device, where the manufacturer has already designed and developed a medical device. In the case of mechanical ventilators, these tests can, for example, involve artificial lung simulations or tests in animals (pigs, sheep, etc). Here, the Competent Authority may or may not be contacted, but as a standard procedure the manufacturer informs the Competent Authority as it needs its approval for the next step. Step two consists of clinical trials. These trials are clinical investigations in which the apparatus is used in patients for the first time. In this step, it is necessary to find a clinical institution (hospital or clinic) which – through its ethics commission – accepts the conduct of such a clinical investigation in its facilities. In the third step, a new stakeholder enters the process – the Notified Body (NB). This is the entity to which the manufacturer submits its application dossier with all the technical documentation and clinical investigations reports. This step is considered the most important step in the whole approval process. If the dossier is not correct, the NB issues a set of Corrective Action Requirements (CAR) to the manufacturer. Once all CARs are addressed,

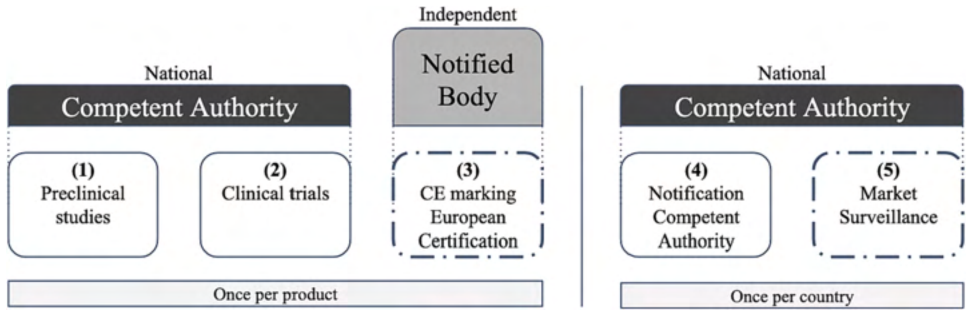

Fig. 1. Approval process steps according to European regulation for the introduction of a new Medical Device in the market of European member states.

the product is finally given the CE marking by the NB, and the medical device has officially finished the first stage of this approval process, according to EU regulation.

The second stage starts with a notification from the manufacturer to the National CA through the submission of a Declaration of Conformity. Along with the notification, at this point, the manufacturer adds any further National requirements for market approval (Step 4). Once this is done, the manufacturer can introduce its device in that specific market (Step 5) but is subject to the enforcement by the National Competent Authority of device recalls; requirements for modification of devices in use; requirements for modifications to future device design, components, or manufacturing processes; and requirements for modification to labelling or instructions for use (Altenstetter, 2003). Steps 4 and 5 need to be followed for every new market into which a product is to be sold. This means that having a product approved, for example, in Germany, does not grant permission to sell that same product in France. The manufacturer (or distributor) has to contact the French Competent Authority and repeat Steps 4 and 5 as the CE marking obtained in Step 3 is valid within all the countries in the European Union.

The final steps from each stage (Step 3 and Step 5) are ongoing processes (hence the dash-pointed line in Fig. 1). For example, the CE marked (Step 3) is a certificate of conformity that is only valid for a period of up to five years (The European Commission, 2017), after which it must be re-applied for. The manufacturer must also be in constant contact with the NB for the notification of adverse events and on-site audits through its time on the market (The European Commission, 2017). Similarly, under Step 5, a manufacturer remains under the surveillance of the Competent Authority as long as it markets its products.

3.2. EU measures for adapting regulation

In the European regulatory framework, there are two ways by which pre-defined rules can be relaxed: *Deregulation* and *Derogation*. Deregulation entails the permanent removal of a regulation; derogation conveys "special" permission not to temporarily comply with a rule.[1]

Derogations can be made in a variety of unique contexts – both for individual patients and in a worldwide crises. European regulation has options for patient-specific derogations by the Competent Authorities, such as when a patient needs a specific medical device to survive. In such a case, the Competent Authority would approve that device for that specific patient through a derogation action. In contrast, in the case of emergency manufacturing of intensive care unit mechanical ventilators, the derogations put in place were due to a worldwide pandemic threatening public health. To understand how entry barriers to the mechanical ventilator market varied by EU country during the COVID-19 pandemic, it is necessary to comprehend how each competent authority used MDD articles n°11 point n°13 or MDR article n°59 in their national context (The European Commission, 1993, 2017).

Due to the COVID-19 pandemic, global production of mechanical ventilators, which stood at 77,000 in 2019, skyrocketed almost twelvefold. By April 2020, the worldwide need for mechanical ventilators was estimated to be 880,000 units (GlobalData, 2020).

The US alone had made contracts with several big firms in the medical ventilation industry totalling 187,000 units – e.g. more than twice the prior year's global demand (Azar, 2020). With global supply chains stretched beyond capacity, countries struggled to get access. Those countries which were fastest in arranging contracts were often the most successful in securing ventilators. With international procurement challenging or impossible, countries found themselves forced to turn to their domestic capabilities. However, for new products from new manufacturers to enter the medical market quickly enough to save lives during the crisis would require moving faster than the norm for the procedures exhibited in Fig. 1.

4. Methods and data

We perform a two-country comparative case study (Yin, 2009; Wonglimpiyarat, 2016) in Europe, comparing Portugal and Spain's regulatory responses to encourage the domestic manufacture of mechanical ventilators. A meaningful comparative case study should consider similar variables for the contextualization of the problem at hand as well as different variables for its conclusions to be relevant (Eisenhardt, 1989).

First, both countries are part of the same economic union and under the same regulatory framework which means that, like every country within the European Union, they have the same mandatory regulatory institutions. The free flow of money and goods within the Union creates an environment where not every country needs to have its own domestic production of every product. Only a handful of countries in Europe have internal production of mechanical ventilators, while others have to import from within or without the Union. While the two chosen countries do not have well-known mechanical ventilator markets, Spain did have two small domestic manufacturers, one of which primarily sold to Spain, while the other essentially marketed its product as exports. Before the COVID-19 outbreak in Europe, Portugal did not have a national manufacturer of mechanical ventilators. Portugal relied on external manufacturers and their representatives (regional suppliers) who provided national technical assistance for these devices. Despite some local manufacturing, the Spanish market was also dominated by large international firms with regional suppliers handling technical assistance. However, in the case of Spain, there were two small domestic manufacturers, one of which primarily sold to Spain, while the other essentially marketed its product as exports.

In addition to their differences in pre-COVID manufacturing, there are several other important differences between Portugal and Spain. As of 2019, Spain had about four times more population (46,9 Million to 10,8 Million (Eurostats, 2019)) and around 6 times higher GDP than Portugal (1393 Trillion € (Worldbank, 2021b) to 239,5 Billion € (Worldbank, 2021a)).

[1] Here, derogation measures can, for example, include activities such as those undertaken under the U.S. Food and Drug Administration's Emergency Use Authorization (EUA).

We use grounded theory-building methods (Strauss and Glaser, 1967; Eisenhardt, 1989) to gain insight into the role of each country's competent authority and the corresponding reactiveness of existing industrial and technological National entities. We triangulate (Jick, 1979) quantitative archival data such as the change in market structure and targeted policies and regulations over time; and a set of 61 semi-structured interviews with new-entrant organizations, incumbent firms, regulatory institutions, and facilitator organizations totalling 49 h of interviews. We have striven to achieve institutional variation with our interview opportunities in each of the countries presented in Table 1. In each country, there were initiatives to develop ventilators, incumbent firms, regulatory institutions, and facilitator organizations. On the one hand, we have contacted each regulatory institution and facilitator organization present in the mechanical ventilators market to understand the institutional differences between countries and the different national policies. On the other hand, we interviewed new entrants and incumbent firms to understand the impact and relevancy of those policies. Furthermore, we interviewed four new entrant initiatives in both Portugal and Spain to account for differences in new entrants' organizational types. We were careful to interview more than one person within each new entrant in order to collect different perspectives from different departments of these organizations and, when appropriate, from their partners. In particular, we interviewed medical doctors who took part in the initiatives of several new entrants. We did this to gain technical insight into medical aspects related to these devices, complementing the engineering perspective of the new entrants. The interview protocol followed for each of these organizations is reproduced in the annex.

5. Findings

5.1. Pre-COVID national contexts and governmental actions

Key players in the ventilator industry ecosystem include regulatory institutions, manufacturers, and industry associations. European regulation requires that some entities, such as Competent Authorities, must exist in every country, but others, such as Notified Bodies or Manufacturers, need not. We find that, prior to COVID-19, both Portugal and Spain had different internal competencies in evaluating, producing, and developing mechanical ventilators. As there is no European or country database on mechanical ventilator manufacturers, we interviewed the medical technology manufacturers association of both countries to gain insight into each national context. We found that before the COVID-19 pandemic Portugal did not have any manufacturer of mechanical ventilators. There was, however, a manufacturer of oxygen generator stations for hospitals – a very closely related industry sector. This manufacturer managed to leverage its regulatory knowledge and technical expertise to produce a mechanical ventilator. A similar example was found in Spain. In addition to the two small manufacturers of mechanical ventilators, there was a firm that produces oxygen-therapy machines that managed to develop a mechanical ventilator. In addition, Portugal had no NB or ventilator manufacturer. In contrast, while modest in scale, Spain had the benefit of both types of entities in its national territory at the time COVID-19 reached Europe. (Table 2).

We discuss first each country's use of their NB by any on-shore manufacturers. As noted above, Portugal does not have an NB or a mechanical ventilator manufacturer. Spain has one domestic NB which was used for original pre-COVID certification by both of Spain's domestic ventilator manufacturers (importantly, the domestic NB is not just for mechanical ventilators). In our interviews with the Spanish incumbent manufacturers and the only Spanish NB, the manufacturers reported that cultural similarity, the same mother tongue, and physical proximity all played a role in companies preferring to use their domestic NB for the original certification. The international dimension inherent in the European regulatory framework does not mandate that manufacturers use a national NB. Indeed, in the past decade, one of the Spanish manufacturers decided to have the conformity assessment of its products made by an Italian NB due to its "*international presence and (the fact that it is) known by our European clients*" – according to the company's CEO and the R&D director.[2]

Firm associations can also be important institutions in a national response. In addition to the NB, in both Portugal and Spain, there is an association that represents the medical device industry and its distributors and manufacturers: In Portugal this association is Apormed. In Spain it is Fenin. These two associations are also associated with the European Trade commission for the medical technology industry, Medtech Europe.

The Portuguese and Spanish governments made different uses of their respective national institutions (Competent Authority and firm associations) to help their domestic industrial and technological entities to produce mechanical ventilators for their hospitals.

Spain took a three-prong approach to its ventilator shortage: it sourced ventilators and components therefore from abroad, it ramped up its existing domestic manufacturers' production of ventilators, and it created conditions to support new ventilator entrants. The Spanish Ministry of Industry made use of Fenin to help ramp up the production of their two small national manufacturers and to help secure an airlift from China to Spain to supply medical equipment including masks, gloves, ventilators, and necessary components for ventilator production. Spain leveraged its COTEC foundation to boost National initiatives on mechanical ventilator development, and create conditions for National initiatives to spur the development of ventilators. The medical ventilator market is highly regulated, and the timeframe to introduce a product in this market is "*normally a matter of years, not months.*" – as clarified by the Executive Manager for Certification's Area of the Spanish NB. While the Ministry of Industry has no direct responsibility in the regulatory process, it was able to take advantage of the COTEC Foundation to serve as a "broker" and help to facilitate more than 80 initiatives to produce mechanical ventilators. On March 30th, the Spanish COTEC Foundation promoted a video conference call between the groups interested in developing mechanical ventilators and AEMPS, the Spanish regulatory authority. This two-hour videoconference created an unprecedented channel between a regulator and the interested industry and research investigators where they could directly ask the head of the medical devices department their questions.

The Portuguese government took a different approach. Limited by its lack of national ventilator manufacturers, there was no visible collaboration between the Government and its firm associations. In 2020, the Portuguese government acquired Chinese ventilators from a company that does not have representatives in Portugal. As a consequence, there were no technicians to set up this equipment or to train medical teams. The Government therefore instead relied on SUCH, the Common Use Service of Portuguese Hospitals, to do this and to provide technical support for these ventilators. The Portuguese Government did not make use of Apormed either to find a ventilator manufacturer or to find a firm to provide technical assistance.

5.2. Adaptive regulatory measures

Both Portuguese and Spanish Competent Authorities implemented derogation measures with the intent to support the national initiatives to introduce mechanical ventilators in domestic hospitals. The Spanish Government's derogation measures, implemented in direct collaboration between different ministries of the Spanish Government and its National institutions, dramatically shortened the process to introduce new the mechanical ventilator while still maintaining safety standards. In contrast, no direct collaboration occurred between the Portuguese Government and its National institutions, and the requirements of the

[2] Here, and subsequently, all direct quotations from interview are reported in italics.

Table 1
Interviews conducted with New Domestic Entrants, Incumbent Domestic Suppliers and Manufacturers, and National Structure Institutions from Portugal and Spain.

Country	Theoretical dimension		Organization type	Interviewee role
Europe	Facilitator 1		European Trade Association for Medical technology industry	Senior Manager Market Data & Officer Market Data
	Facilitator 2		European Innovation Council	Head of the medical technologies program
	Facilitator 3		European Comission, DG - Health and Food	Official - Principal Administrator, Policy and Legal Officer
	Facilitator 4		European Comission DG - Health and Food	Deputy Head of Medical Devices unit
Portugal (No Domestic Manufacturers Pre-COVID))	New Domestic Entrant	New Entrant 1	Non-profit Research Center	Lead investigator
		New Entrant 1	Non-profit Research Center	Head of Licensing
		New Entrant 1 (industrialization partner)	Private Firm	CEO & founder
		New Entrant 1 (Supply partner)	Private Firm	Head of Sales
		New Entrant 2	Non-profit Research Center	Director
		New Entrant 3	University Research Center	Researcher
		New Entrant 4	Private Firm	CEO and founder
		New Entrant 4 (Know-how partner)	Public & Private Hospital	Intensivist MD
		New Entrant 4 (Know-how partner)	Hospital	Pulmonologist & Intensivist MD
		New Entrant 4 (Know-how partner)	Hospital	Intensivist MD
		New Entrant 5	Portuguese Armed Forces	Head of Innovation
	Incumbent Domestic Supplier	Supplier 1	Private Firm	CEO and founder
		Supplier 2	Private Firm	CEO and founder
		Supplier 3	Private Firm	Technical and Commercial director
		Supplier 4	Private Firm	Country general director & Country Commercial Manager
		Supplier 5	Private Firm	ICU Director
		Supplier 6	Private Firm	Vice-director & Head of Sales
		Supplier 7	Private Firm	Country Manager
		Supplier 8	Private Firm	Head of Clinical Sales Support - Respiratory Care
	National Structure Institution	Facilitator 1	Association of Medical Devices enterprises	Regulatory Affairs Technician
		Facilitator 2	Portuguese Business Association	Board member
		Facilitator 3	Medical Doctors Association	President and Medical Doctor
		Health care provider 1	Hospital	Head of pediatric ICU
		Health care provider 2	Hospital	Anesthesiologist MD
		Regulatory institution 1	National Competent Authority	Responsible for the Health Products Directorate
Spain (Two Domestic Manufacturers Pre-COVID)	New Domestic Entrant	New Entrant 1 (Know-how partner)	Private firm	Pulmonologist & Medical Director
		New Entrant 2	Non-profit start-up	CEO & founder
		New Entrant 2 (industrialization partner)	Private Firm	Robotics engineer and project leader
		New Entrant 3	Private firm	CEO & co-founder
		New Entrant 3 (industrialization partner)	Private Firm	Project lead engineer
		New Entrant 4	Public Hospital	Medical Doctor, Cardiologist
		New Entrant 4	University	Head of department & Professor of Electronics
		New Entrant 4	University	Associate Professor of Electronics
		New Entrant 4 (industrialization partner)	Private Firm	Factory Director
	Incumbent Domestic Supplier	Supplier 1	Private firm	Country general director
		Supplier 2	Private firm	Vice-director & Head of Sales
		Supplier 3	Private firm	Ex-Country Manager, current Marketing Director Western Europe
	Incumbent Domestic Manufacturer	Manufacturer 1	Private firm	Senior manager and medical doctor
		Manufacturer 1	Private firm	CEO; R&D Director (written response)
		Manufacturer 1 (Industrialization partner)	Private firm	Product development Director & partnership manager
		Manufacturer 2	Private firm	CEO and founder (written response)
	National Structure Institution	Facilitator 1	Health technology association	Technical Director & Responsible for medical equipment sector
		Facilitator 2	Nonprofit private innovation organization	General Director; Responsible for medical equipment sector
		Facilitator 3	Certification laboratory	Technician of EMC trials
		Facilitator 3	Certification laboratory	EMC Laboratory manager
		Facilitator 4	Certification laboratory	Medical Devices Manager
		Regulatory Institution 1	National Competent Authority	Deputy Director of the Department of Medical Devices, high pharmaceutical technician, and the chief of clinical investigation services.
		Regulatory Institution 2	Notified Body	Executive Manager for Certification’s Area

Table 2
Mechanical ventilator market national structure and corresponding internal competencies per country.

National structure	Internal expertise	Country
Competent authority	Regulatory knowledge (clinical investigations)	Portugal & Spain
Notified body	Technical knowledge (conformity assessment & possible medical devices evaluation)	Spain
Certification laboratories	Technical knowledge (medical devices evaluation)	Portugal & Spain
Firms associations	Information centralization	Portugal & Spain
Ventilators manufacturers	Production of Mechanical Ventilators	Spain
Medical devices Manufacturers	Production of any Medical Device	Portugal & Spain
Innovation associations	Innovation knowledge	Portugal & Spain
Research centers	Technological knowledge (in other areas)	Portugal & Spain

pandemic regulatory process remained much the same as pre-pandemic.

The adaptive regulation measures (i.e. derogation measures) available to both Spain and Portugal considered in this investigation concern the relaxation of the standard steps to introduce medical devices (Fig. 1) in European markets. As contemplated in MDR article n°59, such derogation measures can only be implemented within the country's national territory and must be reported to the European Commission and remaining member-states (The European Commission, 2017).

On March 13th, the European Commission released a recommendation that advocated for a general derogation of the rules which prevented targeted products from accessing the market (Commission, 2020). This EU recommendation initiated a wave of derogation policies across EU member-states. As there was no one-size-fits-all solution executed by the European Competent Authority, there emerged a diversity of adaptations to the established regulation across Europe. Fig. 2 and Fig. 3 show the different implementations of the European recommendation by the two European countries considered in our study. Fig. 2 provides a timeline of the different mechanical ventilator relaxation actions in Portugal and Spain. Portugal was slower to adapt its regulation and slower to remove that adaptation: The Portuguese derogation measure was still active one year after its implementation. In contrast, Spain moved faster both in enacting its regulatory adaptation, and – once its goal was achieved – in removing it. In Spain, the regulatory adaptation only lasted for three months – the same amount of time as its National emergency state (Sanidad, 2020).

A key difference between Portugal's and Spain's derogation

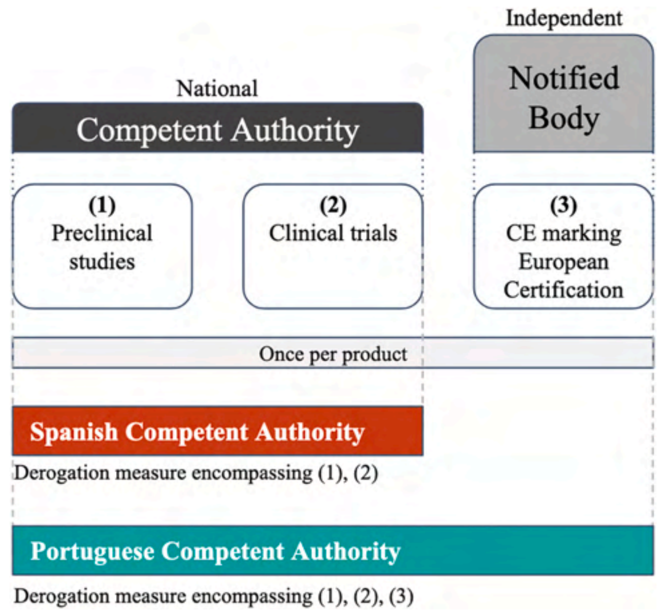

Fig. 3. Differences in the comprehensiveness of each derogation measure.

measures is the context they cover. The Spanish Competent Authority, AEMPS, focused on creating conditions for an extraordinary clinical investigation to be conducted with the healthcare players who decided to participate. This clinical investigation had very strict criteria for inclusion and exclusion. It only covered people with COVID-19-induced pneumonia without other access to ventilatory therapy. Hospitals and clinics that wished to acquire such medical devices had to state their interest and demonstrate their need to AEMPS along with approval from the institution's ethics commission. Without such notification and approval, a hospital could not access to the new ventilators approved under the derogation even if it needed them.

The Portuguese derogation measure did not have this constraint. Once a product was approved by its competent authority any Portuguese hospital could get access to it without the "registration" of each hospital required by Spain. In this sense, the Portuguese derogation measure was similar to a CE-marking approval but only valid within Portugal. This difference in approaches is essential for understanding the outcomes of each derogation measure and its specifics. Fig. 3 illustrates the differences between the comprehensiveness of the derogation measures, mapping them against the "once per product" steps previously outlined in Fig. 1.

Although there is an NB in Spain, Spain's Competent Authority

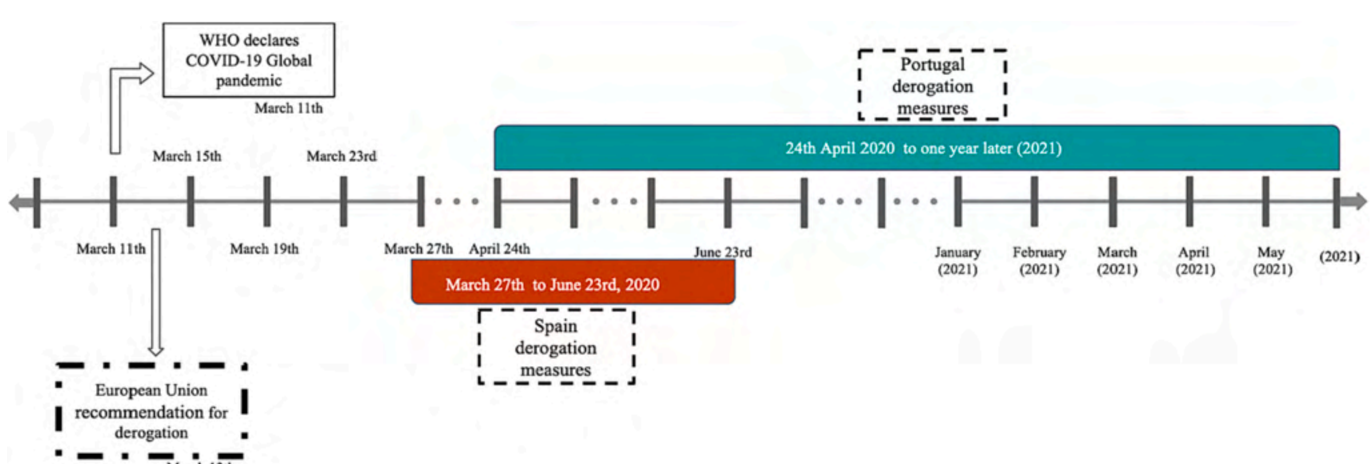

Fig. 2. Timeline of Portuguese and Spanish derogation measures for market access of mechanical ventilators.

devised a derogation measure that did not require its intervention. The opposite is true for Portugal where, while there is no domestic NB, the implemented derogation measure required such competency. The decision to resort to internal or external expertise is controlled by the Competent Authority as this is the entity responsible for the approval under a derogation (The European Commission, 2017). Due to the type of derogation measure it implemented and its lack of a national NB, the Portuguese Competent Authority nominated a Taskforce made of experts (3 engineering professors + 4 Intensivists Medical Doctors). This Taskforce stood in place of a NB for the period of the derogation to assess the conformity of the mechanical ventilators submissions. The Taskforce then advised the Competent Authority whether to approve them or not.

While both the Portuguese and Spanish derogation measures cited the Rapidly Manufactured Ventilator System (RMVS) document by the UK competent authority (MHRA, 2020), the Spanish regulatory action considered requirements such as “a brief risk analysis” (AEMPS, 2020). This lack of clarity was felt by the Spanish initiatives making them rely on international standards, norms, and other documents. One founder of a Spanish initiative explained that the national regulatory entity “*…did not tell us exactly what they needed. We had to come up with a design and present it to them. That is why we resort to the document from the UK authority*”. In contrast, the Portuguese derogation measure was a copy of the existing essential-requirements checklist of the European directive established at the time which is composed of 111 elements (The European Commission, 1993). A c-level manager from a Portuguese research center explained that *“since no one in Portugal has ever regulated a ventilator and making a decision on it might prove to be precedent-setting, and no one wants to open a precedent”*, and while Portugal is integrated in the European regulatory framework, its national regulators did not have domestic production of mechanical ventilators pre-COVID to overview. In other words, a firm that would follow the requirements of the Portuguese regulatory adaptation could get a CE marking for its product if it applied directly to a European certification (provided that it was a certified medical devices manufacturer or was in line with the QMS).

5.3. Outcomes

The regulatory adaptations in Portugal and Spain were different at their core and yielded distinctly different results. On March 27, 2020, while COVID-19 cases were still rapidly rising in the country, Spain adapted its regulation to encourage new ventilator entrants. It took Portugal one more month to adapt the European regulation to encourage new ventilator entrants in April. Fig. 4 shows which phases of the initial COVID-19 outbreak, each National Competent Authority implemented their adaptation of the established regulation and allowed mechanical ventilator new entrants to fulfil the unmet national demand. While Spain acted in the face of considerable uncertainty, at a time when the initial COVID-19 wave was still growing, the Portuguese NCA waited one more month, after the rate of new cases had subsided due to the COVID-19 national lockdown. In that month, Spain had approved 12 new entrants in its national market allowing it to better react to its underserved national market. With its more extensive regulatory requirements (including the equivalent to CE approval), Portugal approved its first and only ventilator entrant more than seven months after its regulatory adaption in December 2020, and Portugal has approved no additional entrants since.

Compared to Spain, Portugal was more exposed to a potential shortage of mechanical ventilators in its hospitals, but its derogation measure was far less successful. Portugal’s only new ventilator initiative approved under the derogation measure faced challenges. In midsummer 2020, Portugal’s sole approved new mechanical ventilator was actually not given an approval by the designated Task-Force; however, the Portuguese Competent Authority over-rode the task force and still authorized its use under certain conditions. One of these conditions was that the ventilator could only be used for patients who did not require constant pressure in the expiratory airway. This requirement means it could not be used in COVID-19 critical patients. This approval for limited use was later overturned on December 30, 2020, in this way completing the medical device approval under the Portuguese adaptation.

The complexity of Portugal’s derogation measure and the lack of transparency by its competent authority to entities not in the ventilator medical device sector were cited by respondents as critical barriers to new entrants. Indeed, the only successful new entrant from Portugal during the first year of the pandemic chose to enter the market through the standard European Union procedures and avoid the Portuguese derogation measure altogether. While this ventilator was developed

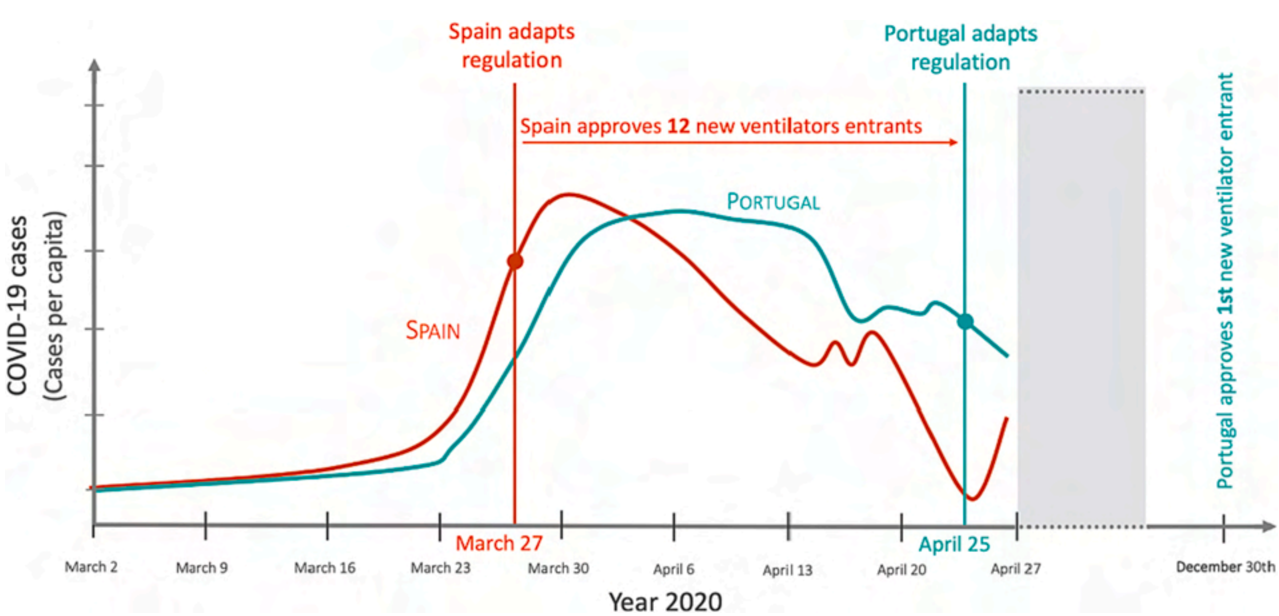

Fig. 4. Differences in adaptation reactiveness and success between Portugal and Spain (Numbers of cases are shown in order to indicate the stage during the pandemic when regulatory action was taken. Given different treatment strategies, and other differences between the two counties, drawing causal inferences about date of regulation and cases or deaths would be inappropriate).

during the pandemic in 2020, this first-ever domestic mechanical ventilator manufacturer in Portugal did not pursue the Portuguese “fast-track” regulatory option as the firm judged that the derogation had the same difficulty level as obtaining the CE-mark (EU certification). There were, in fact, two initiatives in Portugal that decided to avoid the Portuguese adaptation and apply directly for the European certification. In the case of Spain, its adaptation of regulation channeled at least three of the 12 approved initiatives to the European certification. Fig. 5 provides an overview of the different pathways taken by the ventilator initiatives in Portugal and Spain.

While the Spanish Competent Authority was advised by its NB in the formulation and validation of the set of 8 main requirements (AEMPS, 2020) that these initiatives had to follow; the Portuguese competent authority had to fully rely on external help for the conformity assessment. Portugal’s nominated task force was put in a difficult position as it was given the job of providing an independent verdict per product. (INFARMED, 2020); however, its constituents were not from an NB nor had they ever worked in one. When asked about the nomination process, the Portuguese authority clarified that its main concern was the potential conflict of interests of its members which were engineering professors and medical doctors. And yet, this concern seems lower-order than the quality of the task force’s assessment: As no member of this task force had ever worked in an NB, the Portuguese competent authority lacked advice from individuals that matched the medical devices directive’s requirements of “*sound vocational training……satisfactory knowledge… and … adequate experience*” (The European Commission, 1993). This type of vocational training and on-the-job experience is particularly important for ventilators given the tacit knowledge required both for their set-up and operation. This Portuguese lack of domestic expertise was also, according to the interviewees one of the reasons why the Portuguese derogation measure was less dramatic than the Spanish one and more in line with normal non-crisis regulatory requirements.

According to an industrial partner of one of the incumbent manufacturers, the Spanish success in ramping up existing manufacturing and supporting new entrants to fill remaining gaps was due to the fact that Spain “*had the technology and knowledge to develop ventilators in-house, it had our firm, which managed to ramp-up the existing production, and had a Government which smoothened the procurement process and invested in the national industry*”. With Spain’s domestic manufacturers fulfilling most of the national demand, the need for new entrants to fill shortages remained minimal. Indeed, the opportunity may have existed to ship those to other European countries with shortages.

In sum, the way Spain implemented its derogation measure gave it more visibility into the country’s problems and control over its approvals. The Spanish Competent Authority was aware of which hospitals were conducting clinical investigations under the derogation and only COVID-19 patients without access to any other ventilator were eligible (with the consent of their families). The 12 initiatives were only accepted in the first month of the derogation measure, and specifically to address patients in need of ventilators and without access to standard approved ventilation. All four of the Spanish initiatives that we interviewed expressed frustration at their limited use. That said, these initiatives are still able to go through the normal regulatory process in addition. Because of their approach to regulation, the Spanish competent authority made sure it had 12 initiatives prepared to roll out mechanical ventilators if the curve of the daily cases would continue growing. Indeed, the units produced by a Spanish car manufacturer (made from the electric motor of the windshield wiper) are, until today, stored in its warehouse waiting for another surge in cases. It is also worth noting that, all initiatives we have talked with, in both countries, stated that they would be ready to start producing again if necessary.

Additionally, while not elaborated in this paper, we have studied two other European countries, Netherlands and Germany, to understand their regulatory response to the possible shortage of mechanical ventilators in their hospitals. As with Portugal, the Netherlands had no domestic mechanical ventilator producers. Conversely, Germany had a strong mechanical ventilator industrial base that included one of the biggest mechanical ventilator manufacturers in the world. Table 3 compares Portugal, Spain, the Netherlands, and Germany in four different dimensions: their national context, derogation measure implemented, type of regulatory adaptation, and the number of approved new entrants by the end of the adaptive regulation program.

Both Portugal and the Netherlands implemented a nationwide certification facilitating any hospital within their country to get access to any approved ventilator. The Netherlands however, managed to adjust their requirements allowing it to have three approvals instead of just one with its adaptation of the European regulation. In contrast, due to the domestic context of Germany (second highest number of ICU beds per 100,000 inhabitants in the European Union (EUROSTAT, 2018) and

Table 3
Addressing national shortages of different types of products.

Addressing shortage of:		Product safety relevance	
		Non-critical	Safety-critical
Product complexity	Complex	International trade E.g. Wind turbines, solar	Dynamic Regulatory Capabilities needed E.g. ventilators
	Simple	International trade E.g. potato chips	Access might be Sufficient E.g. masks

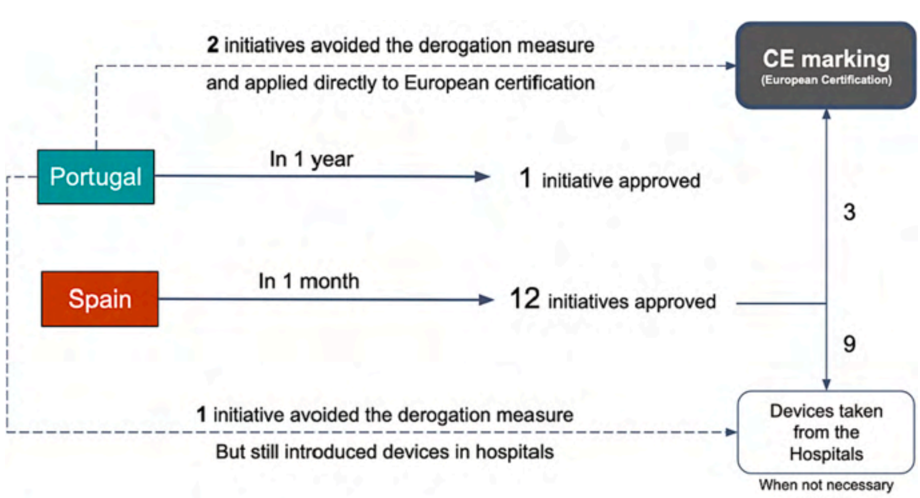

Fig. 5. Different paths to certification of Portugal and Spain ventilator’s initiatives.

strong industrial base of mechanical ventilator manufacturers), there was no adaptation of the established regulation. For this reason, there was no new entrant in the country during the COVID-19 pandemic.

6. Discussion and policy implications

Existing literature has focused on firms' core competencies (Prahalad, 1993; Coombs, 1996) and dynamic capabilities (Teece et al., 1997; Eisenhardt and Martin, 2000; Helfat and Peteraf, 2009; Pisano, 2017). In contrast, our country comparative case study unpacks how *national* domestic core competencies are critical to a *country*'s dynamic capabilities for a response during a national crisis. In this section, we draw on our empirical evidence to propose new theory on which national core competencies matter, for what contexts, and why.

Our research demonstrates for the first time the importance of pre-crisis domestic manufacturing capabilities for dynamic regulatory capabilities during times of crisis. Such capabilities can be essential to responding flexibly during crises to new demand, to new technologies, and to new firm entrants. In times of global crisis or shortages where existing firms are slow or unable to meet global demand, new entrants can play a particularly important role in a country's ability to respond to changes in demand and protect its citizens' social welfare. In cases where product regulation is essential to safety, regulators require sophistication to act quickly and flexibly without endangering patient safety, especially as new firms (and sometimes established firms with new products) may lack the capability to consistently produce a safe product.

Our empirical findings show that domestic production capabilities can be helpful in developing domestic regulatory capabilities. The existence of manufacturing within a country requires its regulation, so those that have manufacturing companies on their home turf have more resources and knowledge related to regulating it. Our findings further suggest that the existence of domestic manufacturers may be helpful not only in providing static regulatory capabilities but also in providing dynamic regulatory capabilities. These findings may be true regardless of firm size. Even though Spain did not have a major domestic manufacturer of ventilators, by having two small domestic manufacturers of ventilators, it was better able to regulate new ventilator entrants than Portugal - which lacked any domestic ventilator manufacturers at the start of the pandemic. These findings indicate that there may be significant value to countries maintaining domestic manufacturing in products critical (e.g. with sufficient magnitude of returns) to national security or social welfare, even if small or economically not meaningful.

In light of this finding, a challenging question becomes: in which technologies or products should a country invest to maintain these costly capabilities. Similar to past work on the regulation of products with high uncertainty and tacit knowledge (Bonnín Roca et al., 2017), we argue that domestic manufacturing of such products may be particularly important for their regulation. Based on our findings, we propose new theory for which types of products it may be particularly important to maintain domestic manufacturing capabilities in order to have dynamic regulatory capabilities. Table 3 develops new theory for the characteristics of products, in a national shortage situation, that may require nations to have the internal knowledge to support dynamic regulatory capabilities. As the table shows, we focus on the safety criticality and the technological complexity of the product. Specifically, we propose that countries may not necessarily need to ensure access to products that are not safety-critical, regardless of their level of complexity, as they can rely on international trade. Conversely, a shortage of safety-critical products might prove harder to deal with as other countries might be taking protective measures and not supplying such products. If the product is simple to produce, it can be easier for the existing technological and industrial entities to start producing. However, if the product is complex, our findings suggest that it may be necessary to have access to tacit technical and industrial expertise to adapt the established regulation and other entry barriers inherent to the product so as to facilitate the production ramp-up of domestic manufacturers and to safely accelerate the entry of new manufacturers.

In addressing shortages of a complex and knowledge-intensive life-supporting product, countries without access to domestic technical and industrial expertise are likely to have a harder time implementing the necessary regulatory amendments to help new research and industrial entities address the existing shortages. In our interviews, multiple respondents highlighted the significantly higher complexity of producing ventilators, than face masks. This comparison was made by interviewees to showcase the importance of government knowledge and support in carefully facilitating companies' progress through the regulatory hurdles of ventilator device approval in order to accelerate new entrants. This knowledge is equally important at the firm level. We interviewed a mechanical ventilator supplier in Portugal that, due to the shortage of masks triggered by the pandemic, pivoted from only supplying ventilators to also manufacturing surgical masks in-house. The CEO and founder of this firm explained that "*ventilators are a product that need[s] a lot of know-how and the companies that produce them need people with this know-how*", while for masks "*we just needed to acquire the material and machines*". This example underscores the difference in the magnitude of the challenge to produce a complex product or a simple product in times of crisis. In the case of non-critical products (e.g. where shortages do not present a risk to national defense, economic security, or social welfare), whether complex (e.g. wind turbines) or simple to produce (e.g. potato chips), we propose in our theory that domestic manufacturing competencies are less essential – at least to dynamic regulatory capabilities, and the countries without these domestic capabilities can rely on international trade to fill in the gap.

In Table 4 we focus on the implications of the right column from Table 3 for national strategy. The two main dimensions in Table 4 are the locus of manufacturing and the complexity of the safety-critical products. More complex products require more technical expertise and tacit knowledge to (safely) produce. Having production facilities in a country's territory also increases the likelihood of a nation having dynamic regulatory capabilities: by having manufacturing in a country, the country must have in place a regulatory body to overview that manufacturing. In turn, domestic regulatory experience increases regulatory capabilities to adapt dynamically to new market scenarios so as to facilitate potential new entrants into producing the necessary products. Importantly, in proposing the importance of domestic manufacturing for this table, we focus on dynamic regulatory capabilities. While not the focus of this paper, notably, much research has explored the positive externalities of domestic manufacturing in terms of linkages across sectors (Cohen and Zyzman, 1987), industrial commons (Pisano and Shih, 2009), research expenditures and jobs (Helper et al., 2012) and innovation (Fuchs, 2014; Branstetter et al., 2017). the offshore production of a domestic firm may or may not grant the country of ownership with dynamic regulatory capabilities due to possible rotation between industry and regulatory bodies and other factors (Johnson, 1982; Breznitz, 2007; Fuchs and Kirchain, 2010; Bonnín Roca et al., 2017).

Based on our proposed theory, it is possible to analyze countries' dynamic capabilities to respond to different types of crises and predict which countries might thrive or struggle under distinct conditions. Our research suggests that countries without the core competencies of domestically manufacturing technically complex, safety-critical products will probably not have the dynamic regulatory capabilities to simplify standard regulations which are critical to facilitate new entrants to produce the required products. This inability to dynamically adapt regulation to support new entrants limits a country's response to national shortages of technically complex products critical to national needs. This limited response can in turn result in a lack of ensured access to such products and increased dependency on allies and international private firms and organizations.

Notably, there may be other ways to develop this dynamic capability other than domestic manufacturing, as maintaining domestic

Table 4
Country capabilities relevancy in situations of national shortages of different safety-critical products.

<table>
<tr><td></td><td></td><td colspan="4">Locus of Manufacturing</td></tr>
<tr><td></td><td></td><td>Onshore
e.g. Spain</td><td colspan="2">Offshore
e.g. Netherlands</td><td>Doesn't exist
e.g. Portugal</td></tr>
<tr><td></td><td>Contextualization:</td><td colspan="2">DRC Exists</td><td colspan="2">DRC don't exist</td></tr>
<tr><td rowspan="2">Types of Safety-critical products in shortage</td><td>Complex</td><td colspan="2">Reliable access
(Incumbent firms or New entrants)</td><td colspan="2">Access not ensured</td></tr>
<tr><td>Simple</td><td colspan="2">Ensured access
(Incumbent firms or New entrants)</td><td colspan="2">Not reliable access
(New entrants)</td></tr>
</table>

DRC - Dynamic Regulatory Capabilities

manufacturing can be costly. Further research is necessary to understand if alternative institutional arrangements, including pooled resources that leverage knowledge from other countries that have domestic manufacturers (such as the development of an adaptive EU regulatory body specific to the crises), could bring dynamic regulatory capabilities to countries that do not have their own domestic manufacturers during crises. Such pooled resources would likely be best achieved by allowing countries to enter into explicit pre-crisis agreements to distribute or share these costs. In our interviews with the European Commission and the national Competent Authorities, we have learned that there is an allowance for the Competent Authorities to be trained by international experts. However, this training is currently set up as more of a continuous process than an acute measure to deal with timely problems during crises. There is no crisis process set in place for the necessary support for countries that cannot develop dynamic regulatory capabilities due to their lack of domestic production. In crisis situations where training may be too time-intensive, better may be to have countries with internal competencies directly support the regulation of new entrants in countries that do not. Since such support is time-intensive, agreements between countries with complementary competencies or across unions of countries would be necessary in advance, with reciprocal agreements (for example trading of competencies or general agreements on other safety measures that must be taken to support the union's health as a whole) in place in advance of specific urgent needs.

Past literature has debated the importance of maintaining domestic manufacturing capabilities for prosperity (Cohen and Zyzman, 1987; Acemoglu and Robinson, 2012), jobs (Nelson, 1993), innovation (Branstetter et al., 2017), and access (Breznitz, 2007). We add to this literature the potential importance of domestic manufacturing capabilities for dynamic regulatory capabilities during times of crisis. Here, our research suggests that the existence of manufacturing - rather than its size or capacity - may be the most important contributor to dynamic regulatory capabilities. This finding is especially relevant for smaller countries, such as Portugal, as smaller countries have a harder time providing markets of sufficient scale for domestic manufacturing of a wide range of products (Nelson, 1993). While Portugal might be seen as a standalone example in Europe, similar to Portugal, more than 20 of the 27 European countries did not have a ventilator manufacturer or a Notified body at the time of the COVID-19 outbreak.

Our theory provides a framework for countries to systematically review their potential vulnerabilities and in which products they may wish to sustain minimum domestic competencies and capabilities. More specifically, our theory suggests that countries that can afford to, should re-consider maintaining domestic manufacturing capabilities in select critical products that are critical to national security or social welfare, complex to produce, and high in tacit knowledge; where the expected value (given the probability of a crisis, expected domestic and global demand during these crises, and expected global shortages) exceeds the cost. When assessing the expected value, countries should consider that domestic manufacturing has value not only for access (immediate and dynamic production capabilities), but also new firm and technology introduction (dynamic regulatory capabilities). Here, onshore production partnerships with multinational firms that are not owned by the home country may be equally valuable; thus, our results suggest that there may be additional (previously unaccounted for) value for countries to compete for this foreign direct investment, in the form of dynamic regulatory capabilities. Countries unable to sustain or attract domestic manufacturing, such as small countries with smaller domestic markets and resources, may benefit from partnerships with countries that pre-agree to share expertise to support the safe and adaptive regulation of new home country manufacturers during crises. Our research suggests the EU would benefit from establishing mechanisms to support such agreements immediately: Alone in ventilators, more than 20 European Countries had neither domestic mechanical ventilator manufacturers nor notified bodies with expertise regulating ventilators. In this regard, one regulator from the European Commission notes that "*the commission itself and all the member states learned some lessons and are going to take measures to improve the response for future crisis. We know that, of course, in the future we can face other similarly or worse crisis we hope not to, but we need to be prepared. So, for example, the commission is setting up a couple of new agencies to provide technical assistance and financing*". While Unions of countries such as the European Union are clear places to have institutions to facilitate such sharing, the sharing of expertise we propose could also be undertaken by nations and multinationals outside a particular union - for example, the U.S. and its multinationals could pre-agree to share knowledge to support during crises the regulation of new entrants in safety-critical and technologically complex critical products in other countries.

7. Conclusion

In situations involving national shortages of safety-critical products, creating conditions to ensure product access can be critical to maintaining citizens' safety and welfare. Past literature has debated the importance of maintaining domestic manufacturing capabilities for prosperity (Cohen and Zyzman, 1987; Acemoglu and Robinson, 2012), jobs (Nelson, 1993), innovation (Branstetter et al., 2017), and access (Breznitz, 2007).

We demonstrate for the first time the importance of domestic manufacturing for dynamic regulatory capabilities during times of crisis. Leveraging 60 semi-structured interviews with informants in regulatory bodies, established firms, and new entrants, we find that countries with domestic manufacturing prior to the COVID-19 pandemic were better able to create regulatory conditions to safely accelerate the entry of new domestic ventilator manufacturers during the early days of the COVID-19 crisis. Our results suggest that it is the *existence* of manufacturing, and the tacit knowledge that goes with it, rather than the size or capacity of those manufacturers, that facilitates rapid adaptation of regulation. Our findings in ventilators are especially likely to generalize to other situations involving shortages of technologically complex, safety-critical products, as these are inherently more challenging to produce and to safely regulate the introduction of new entrants. Countries with domestic manufacturing of such products prior to a crisis have experience in regulating those products, and domestic knowledge that they can bring to bear in adapting established regulation to facilitate safely expanding production and supporting new entrants during a crisis. Those that lack this experience may suffer serious delays.

When assessing the value of investing in domestic manufacturing of critical products, countries should consider the additional advantage provided by such prior experience and tacit knowledge during crisis situations. Because it is expensive to maintain manufacturing in several different sectors, small countries that identify potentially critical needs may benefit from establishing pre-crisis partnerships with other countries – both to locate manufacturing in-country during a sudden demand spike and to share knowledge and expertise to adapt regulation to safely support new entrants. Multinational groups, such as the European Union, should act immediately to develop mechanisms to support such agreements across their member states or countries. Other countries with strong domestic manufacturers should likewise consider how they could share knowledge with countries that lack such capabilities in order to support the safe regulation of new entrants during crises.

CRediT authorship contribution statement

Conceptualization – AA, GM, JM, EF; Data curation - AA; Formal analysis - AA; Funding acquisition – GM, JM, EF; Investigation - AA; Methodology – JM, EF; Project administration - GM; Resources - AA, GM, JM, EF; Software - AA; Supervision – GM, JM, EF; Validation; Visualization – AA, EF; Roles/Writing - original draft - AA, GM, JM, EF; Writing - review & editing - AA, GM, JM, EF.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Build It and They Will Come? US Regional Labor Composition & Readiness to Meet Skill Demand Shocks from CHIPS and Science

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Abstract

Expansionary industrial policies, such as the CHIPS and Science Act, are followed with notable surges in labor demand within the industries they target. In the case of the CHIPS and Science Act, industries such as semiconductor manufacturing experienced significant influxes in financial investment, with $231 billion being committed to Semiconductors & Electronics thus far. Recognizing the imperative to address such labor demand shocks, we propose a novel operational methodology. This methodology, informed by economics, assesses potential supply-demand skill discrepancies, and incorporates factors such as the intertemporal occupational rates of transition and regional wage distributions. By analyzing the skill compositions inherent to industry-related occupations, our approach provides a strategic advantage to policymakers and industry stakeholders, enabling them to identify specific U.S. locales with the requisite skill profiles and potential wage structures. Furthermore, the practical application of our methodology is embodied in the Workforce Insights Tool, which offers comprehensive labor insights. To substantiate the efficacy of our approach, we consider the semiconductor manufacturing industry in the context of the CHIPS and Science Act as a representative case study, exploring diverse strategies for the construction of skill profiles for industry-related occupations.

1 Introduction

In the rapidly evolving landscape of industrial policy, the CHIPS and Science Act in the United States stands as a distinctly significant intervention for its scale and comprehensiveness of scope, including a swathe of industrial and job creation objectives, particularly affecting semiconductor manufacturing (Semiconductor Industry Association, 2023a). This act provides for substantial investments in U.S. domestic manufacturing capacity and consequent regional as well as national shocks in the demand for semiconductor manufacturing skills, often in regions of the United States without a significant incumbent semiconductor workforce. Where skill demand is not met, labor is a potential bottleneck on the performance of these capacity investments. Meanwhile, meeting this skill demand in labor markets without an existing semiconductor workforce will require workers who are willing and able to transition from their current occupations into novel roles, posing both a skills matching challenge and a potential opportunity for wage improvements for transitioning workers (Hughes et al., 2021; Fox et al., 2020). In this paper, we apply a novel analytical methodology to identify in which regions and for which skills these workforce constraints may bind on capacity-building, and under what skill-matching conditions the workforce needs to be generated by industrial policy might be met from outside the semiconductor industry or even the manufacturing sector.

We introduce an industry-agnostic analytical methodology to identify potential skill gaps in labor supply and demand, refine candidate occupations for transitions to meet demand, and suggest key skill margins for closing those gaps, especially under the substantial demand fluctuations induced by such policy changes as CHIPS and Science (House, 2022). The methodology uses a comparative framework of the requirements for different occupations and builds on past skill-matching methods to quantify how well a candidate occupation satisfies the requirements of a target occupation, such as semiconductor technicians (parameterized in this paper using the O*NET occupational requirements' database). This framework allows us to identify candidate occupations (within different tolerances) to meet skill demand. By leveraging empirical evidence on intertemporal occupational transition rates and regional wage distributions, we can recover the stock and flow of occupations to satisfy the demands created by industrial policy and other shocks.

We apply this methodology to the semiconductor industry and specifically the new skill demand associated with fab announcements under CHIPS and Science, which offer a significant case study in understanding how government policies can shape skill demands and labor mobility. By focusing on the semiconductor manufacturing industry and the CHIPS and Science Act, we provide a targeted exploration of how skills and regional occupational employment interplay with workforce transformation opportunities in high-tech industries. Our research contributes to the understanding of the readiness of regional labor markets to meet skill demand created by industrial policy, and the key gaps between skills needed and available across regions.

Our work bridges the gap between academic research and practical policymaking, supporting future understanding of potential labor market adaptations in an era marked by rapid technological advancements and policy shifts. Semiconductor manufacturing is a case application for our "Workforce Insights Tool," which offers insights for strategic workforce planning and policy formulation based on our methodology. This tool has broader applications to sectors in which the content of skill demand is changing or novel labor demand shocks (positive or negative) are introduced to labor markets (Blair et al., 2021; Nedelkoska and Neffke, 2019).

2 Literature Review

There has been significant scholarly interest in occupational transitions and discrepancies between skill demand and supply to meet demand shocks (either to fill new roles, or to transition workers whose employment is disrupted, e.g., by technology or policy change). Our study builds on this body of work, uniquely exploring how recent policy changes, such as the CHIPS and Science Act, intersect with labor market dynamics, particularly in high-tech industries such as semiconductor manufacturing (House, 2022).

In assessing the evolving needs of cutting-edge industries, significant insights have been provided by Hughes et al. (2021) and Fox et al. (2020) regarding the quantum industry. Their research underscores the critical role of higher education in aligning with industry demands, especially as new technologies emerge. This alignment, crucial for workforce readiness, highlights the need for educational institutions to continuously adapt their curricula and training programs in response to industry and policy shifts.

Complementing this perspective, Blair et al. (2021) have explored the growing income inequality in the labor market, attributing it in part to skill discrepancies between workers with different educational backgrounds. Their findings highlight the importance of recognizing diverse pathways of skill acquisition beyond traditional education. This understanding of skill acquisition is crucial in addressing labor market inequalities and ensuring that workers are equipped with the relevant skills to thrive in evolving economic conditions. Our study extends this discussion by exploring how policies can target these skill gaps, thereby fostering a more equitable and efficient labor market.

In the realm of skill mismatch and transferability, our study is informed by the works of Nedelkoska and Neffke (2019) and Jiang and Gong (2022). Their research provides a detailed understanding of how skill mismatches can affect labor market outcomes, particularly in times of economic and technological transition. By situating these insights within the context of recent policy changes, we offer a comprehensive analysis of the dynamic interplay between skills, wages, and labor market trends. Our paper examines intertemporal occupational transition rates and regional wage distributions to quantify the potential scope of labor market response to technological shifts and policy interventions.

Alabdulkareem et al. (2018) and Frank et al. (2018) have significantly contributed to understanding the polarization of workplace skills. Their research delves into how different skill requirements between high- and low-wage occupations affect individual and urban labor mobility, a crucial aspect as industries respond to automation and other technological changes. Combemale et al. (2021) further this discourse by exploring the varied effects of technological advancements on skill demand. These insights form a crucial backdrop for our study, which examines the broader labor market implications of such skill polarization and the role of policy in mitigating its potential adverse effects.

Our research not only synthesizes a broad spectrum of existing literature, but ventures into new territory by extending skill similarity measures (traditionally symmetric within occupational pairs) to incorporate differences in the skill *level* of occupations, so that not all transitions are two-way. It breaks new empirical ground by evaluating the readiness of regional labor markets to meet an emerging demand shock created through landmark industrial policy. It also examines the implications of policy changes on skill discrepancies and occupational mobility. It presents a first approximation of the scope of potential labor market or labor-institution response (e.g., through occupational transitions) to labor demand shocks such as technological innovation and policy intervention.

3 Data

The analytical framework of this research is predicated on the utilization of publicly available data, encapsulating a range of occupational characteristics and labor market metrics across the United States. The ensuing subsections provide a detailed exposition of the datasets employed, primarily sourced from the Occupational Information Network (O*NET) database, the Occupational Employment and Wage Statistics (OEWS) program, and the Integrated Public Use Microdata Series

Current Population Survey (IPUMS CPS). These datasets collectively furnish comprehensive insights into occupational skill profiles, employment and wage distributions, and occupational mobility trends, thereby laying a robust empirical foundation for the analysis undertaken in this study. The detailed description of occupational attributes from O*NET, coupled with the granular employment and wage data from OEWS and the longitudinal occupational mobility insights from IPUMS CPS, facilitates a nuanced exploration of the dynamics at play within the U.S. labor market. Subsequent subsections delve into the specific attributes and methodologies inherent to each dataset, alongside a discussion on the data preparation steps undertaken to ensure a coherent and rigorous analysis.

3.1 Occupational Skill Profiles

The comprehensive nature of O*NET's database, maintained by the U.S. Department of Labor, is pivotal in constructing accurate occupational skill profiles. This resource offers a detailed view of the work activities, skills, abilities, and knowledge (WASK) necessary for a wide array of jobs in the United States. The data, sourced through rigorous surveys from job incumbents and experts, is subject to statistical analysis, yielding levels and importance values for each WASK component. These metrics provide a nuanced understanding of job requirements and the competencies critical for effective performance.

O*NET, which replaced the Dictionary of Occupational Titles in 1998, has become a foundational tool in labor market analysis. It allows for the in-depth examination of job roles, essential for understanding labor dynamics. The WASK datasets within O*NET are particularly valuable in this regard. They form the basis for dissecting the competencies associated with specific job roles, a key process in developing comprehensive occupational skill profiles. In our research, we utilize these datasets extensively, as illustrated in Tables A.1, A.2, A.3, and A.4, which detail the characteristics captured by each WASK element.

Levels in O*NET signify the degree of proficiency required in each WASK area for a particular occupation, measured on a numeric scale. Higher values indicate a greater need for skill or knowledge. The importance metric, similarly quantified, reflects the significance of each WASK element in a job. This combination of levels and importance is essential for identifying the specific demands of a job and for highlighting areas where the labor market may be experiencing skill shortages.

The Work Activities dataset within O*NET is instrumental in outlining the tasks and duties of various occupations, categorizing job roles into core activities and evaluating their necessity and importance. This analysis helps identify the pivotal elements of each occupation. The Abilities' dataset focuses on the innate capacities crucial for job performance, like manual dexterity or analytical reasoning, while the Skills' dataset categorizes proficiencies into basic and cross-functional skills, providing insights into the competencies needed across various industries. Lastly, the Knowledge dataset details the specific expertise required in different fields. Together, these datasets offer a comprehensive view of the labor market's competency requirements, facilitating the creation of detailed and accurate occupational skill profiles.

3.2 Occupational Employment and Wage Distributions

The Occupational Employment and Wage Statistics (OEWS) program is a comprehensive survey that collects data on employment and wages for a wide range of occupations in the United States. The survey covers a diverse array of industries and occupations, using the Standard Occupational Classification (SOC) system to categorize job roles in a consistent and coherent manner.

One of the primary objectives of the OEWS program is to provide detailed information on wages for various occupations. The collected wage data includes information on hourly and annual earnings, as well as percentiles such as the median, 25th, and 75th percentile wages. The data is collected at multiple geographic levels, including national, state, and metropolitan statistical and

New England City and Town areas (MSAs and NECTAs, respectively). The geographic breakdown of the data also helps reveal regional patterns and variations in employment and wages, which can be critical for understanding local labor market dynamics and informing regional economic development strategies.

We focus our consideration on the OEWS data for 2021 and 2022 as they provide estimates based "solely on survey data collected using the 2018 SOC" to circumvent inter-taxonomy mapping uncertainties.[1] We exploit the geographic granularity and detailed SOC to identify the national, state-level, and MSA-level occupational employment distributions.

3.3 Occupational Mobility

The Integrated Public Use Microdata Series Current Population Survey (IPUMS CPS) provides a comprehensive, harmonized dataset of the "basic monthly survey" conducted by the Current Population Survey (CPS) involving a series of labor force and demographic questions, with data available from 1976 onwards. Administered monthly to over 65,000 households as a joint initiative of the U.S. Census Bureau and the Bureau of Labor Statistics, the CPS collects data on demographics, labor force status, education, and more. For our application, we rely on the CPS data for estimating occupational mobility at the national level.

The CPS follows a specific rotation pattern, wherein households participate in the survey for a total of eight months. Respondents are interviewed for four consecutive months, followed by an eight-month break when they are not surveyed. After the break, respondents reenter the CPS for another four months. This pattern allows for tracking individuals over time and observing changes in their occupational status. From these survey responses, we compute two levels of occupational mobility statistics: annual and trend. The annual mobility data consists of the observed entry and

[1]2019 and 2020 both implement a hybrid structure of SOC coding, incorporating SOC 2010 and SOC 2018. Information quoted from https://www.bls.gov/oes/soc_2018.htm.

exit rates between origin and destination SOC-coded occupation pairs within a given year, for 2021 and 2022. The trend mobility data computes these rates based on data for both years to capture cross-year transitions. We do not consider years prior to 2021 as they suffer from taxonomy-based issues with the transition to SOC 2018 that we described in Section 3.2.

3.4 Data Preparation

To ensure accuracy in the integration of multiple data sets, we undertook a comprehensive data preprocessing phase to develop the analytical framework.

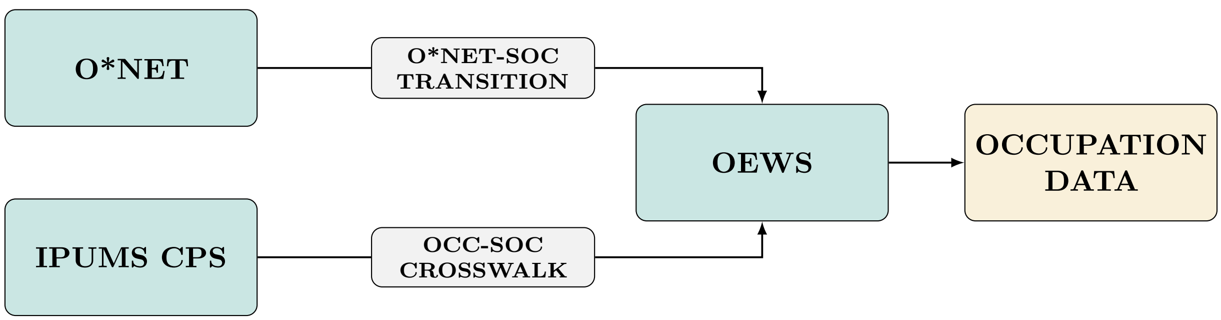


Figure 1: Approach for data preparation

An understanding of the various taxonomies at play is important. Figure 1 presents an overview of the relation between the data we use. The figure demonstrates the role of two transitions that were critical for the construction of the occupation data. The OEWS data, containing annual geographic data on employment and wage distributions by SOC code, functions as our base to which we merge skills, mobility, and demographics data. We begin by merging the skills' data to OEWS. O*NET data is based on the O*NET-SOC 2019 taxonomy, which is directly adopted from the SOC system is assigned the six-digit SOC code, along with a .00 extension.[2] To merge the data, we consider the detailed SOC occupations of O*NET and merge the occupations with OEWS; the resulting data establishes the existing occupations for our analysis.

[2]For more information, see https://www.onetcenter.org/dl_files/Taxonomy2019_Summary.pdf.

The second transition identified in Figure 1 is between the CPS and OEWS. Within the CPS framework, occupations are coded using the Census classification scheme, which does not have a one-to-one mapping with the SOC scheme. The Census classification aggregates SOC codes "if they do not have an exact match to a Census occupation code or to preserve confidentiality in cases where the category contained fewer than 10,000 people nationwide."[3]

The 2018 SOC (Standard Occupational Classification) taxonomy is a hierarchical classification system that groups occupations based on their similarities in job duties, skills, and knowledge. The taxonomy has four levels: major groups, minor groups, broad occupations, and detailed occupations. Broad and detailed occupations are the third and fourth levels of the taxonomy, respectively. Our considerations are constructed such that the framework is operational at the broad and detailed SOC-levels, though we focus on the detailed 6-digit SOC coded occupations for our analysis.[4]

The data provided by O*NET contains information at the detailed SOC level. Broad occupations are groups of occupations that share similar job duties and require similar skills and knowledge. They are composed of a set of detailed occupations that are closely related in terms of their essential job duties. For example, the broad occupation "Management Occupations" includes detailed occupations such as "General and Operations Managers," "Marketing Managers," and "Human Resources Managers." Detailed occupations are specific occupations that are defined by a unique set of job duties, skills, and knowledge. They are the most specific level of the SOC taxonomy and represent the most detailed breakdown of occupations. For example, the detailed occupation "Registered Nurses" includes all registered nurses who perform a defined set of job duties, while the detailed occupation "Critical Care Nurses" includes registered nurses who specialize in critical care settings. To conduct our analysis at the broad SOC level, we need to aggregate the O*NET data. We do so by grouping each detailed SOC to its corresponding broad SOC grouping and computing

[3]See https://usa.ipums.org/usa/volii/occtooccsoc18.shtml.

[4]Information on 2018 SOC Taxonomy available at https://www.bls.gov/soc/2018/soc_2018_class_and_coding_structure.pdf.

the weighted mean and weighted standard errors as follows.

The weighted mean is computed as

$$\widetilde{X}_b = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

and the weighted standard error is computed as

$$\widetilde{SE}_b = \sqrt{\frac{\sum_{i=1}^{n} \left(w_i^2 \cdot SE_i^2\right)}{\left(\sum_{i=1}^{n} w_i\right)^2}}, \tag{2}$$

where n is the number of occupations in each broad category, w_i is the weight for detailed occupation i, which in this case is total employment, x_i is the average value for detailed occupation i, and SE_i is the standard error of occupation i. $\widetilde{X}_b$ is the weighted average skill value for broad occupation b and $\widetilde{SE}_b$ is the weighted standard error for broad occupation b. These are computed for both the importance and level values.[5]

4 Methods

In this section, we outline the computational approach taken to construct our analytical framework. Our analytical methodology consists of three computations: skill similarity, labor supply stocks, and occupational-transitions-based predicted labor flows. We propose a method to compute skill similarity (or skill distance as it has been known in portions of the existing literature), which indicates the degree to which the skill profile of an existing occupation meets the requirements of a test occupation. The computed skill similarities provide the basis for our computation of labor supply stocks and flows.

[5]Skill ratings within O*NET are ordinal variables, which suggests that direct computation of means or weighted averages on their values would be inappropriate. However, ratings within O*NET are sampled from multiple respondents, and incorporate standard error calculations, making it possible to characterize ratings as sample measures susceptible to aggregation.

4.1 Skill Similarity

Skill similarity captures the degree to which the skill profiles between two occupations are similar, which we argue identifies the extent to which the occupational requirements of one occupation may be met by employees of another occupation. We focus our computations on the level of skills, as importance does not signal capability of the workers, but the degree to which having a particular level of competency is necessary for success in a given occupation. For the computation of skill similarity, we consider two certainty options to determine the degree of skill similarity: a) the extent to which the average skill levels required by a test occupation are satisfied by the existing occupation average skill levels or b) the extent to which the bounds of skills' levels required by the test occupation are satisfied by the average skill level of the existing occupation, where bounds are constructed using one standard error above and below the average level. We consider both options as they provide a choice in the rigidness of skill requirements of prospective existing occupations, with the mean-based computation presenting less stringent requirements of prospective employees by placing a minimum requirement of competency in skills.[6]

We compute skill similarity as follows. Let $\boldsymbol{X}$ be a set of skill vectors (as captured by WASK) that constitute existing occupations, and let $\boldsymbol{Y}$ be either a subset of $\boldsymbol{X}$ such that each occupation in $\boldsymbol{Y}$ is also present in $\boldsymbol{X}$ and thus an existing test occupation, or $\boldsymbol{Y}$ can be a user-defined test occupation. For each occupation vector $x \in \boldsymbol{X}$, let $\text{AVG}i^x$ be the average level of a particular skill i across all workers in occupation x. Similarly, for each occupation vector $y \in \boldsymbol{Y}$, let AVG_i^y be the average level of the same skill i across all workers in occupation y, and let SE_i^y be the standard error of AVG_i^y.[7]

[6]An additional tradeoff of the two approaches is that, while the mean approach may identify over-skilled existing occupations, the bounded approach relies on users to have standard errors in their test occupation profiles in the event they are constructing their own.

[7]For some occupations in the O*NET data, there are missing standard error values which we set to 0 for the purposes of our analysis.

We define the indicator function $\mathbb{1}(x)$ for the case of mean certainty as follows:

$$\mathbb{1}(x) = \begin{cases} 1, & \text{if } \mathrm{AVG}_i^x \geq \mathrm{AVG}_i^y \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

In the case of bounded certainty, we compute:

$$\mathbb{1}(x) = \begin{cases} 1, & \text{if } \mathrm{AVG}_i^x \in \left[\left(\mathrm{AVG}_i^y - \mathrm{SE}_i^y\right), \left(\mathrm{AVG}_i^y + \mathrm{SE}_i^y\right) \right] \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

This condition in the indicator function evaluates whether the average value of a given skill i for existing occupation x falls within a reasonable range of skill levels, defined as one standard error away from the average level of skill i for test occupation y.

To compute the skill similarity percentage between occupations $x \in \boldsymbol{X}$ and $y \in \boldsymbol{Y}$, we use:

$$\text{Skill Similarity}_{xy} = \left[\frac{1}{|\boldsymbol{Y}|} \sum_{x \in \boldsymbol{X}} \mathbb{1}(x) \right] \cdot 100\%, \tag{5}$$

where $|\boldsymbol{Y}|$ denotes the number of unique skills within $\boldsymbol{Y}$. This equation computes the average value of the indicator function $\mathbb{1}(x)$ across all skills in $\boldsymbol{Y}$, expressing the result as a percentage.

The cosine similarity formula is considered in our analytical framework when assessing the similarity between two skill vectors in a multidimensional space. In the O*NET data context, workers from different occupations might perceive the importance of skills differently, potentially leading to inconsistent and inaccurate skill importance values. Moreover, the data, typically derived from fewer than ten respondents per occupation, is likely to suffer from response bias. To mitigate these issues, we provide the option to incorporate the cosine similarity measure in our analytical framework as presented in Equation (6), focusing on the direction rather than the magnitudes of skill vectors (Blair et al., 2021). This approach allows us to compare the relative importance or level of skills across different occupations accurately, even when absolute values are inconsistent, thus identifying transferable skills and providing insights into skill relevance in various occupational contexts.

Given the versatility of this method, the cosine similarity can be computed for either the importance or level of skills, denoted by the superscript m in the equation. We also allow for the choice of computing on both metrics. The cosine similarity measure is computed as follows:

$$\text{Cosine}^m(x, y) = \frac{\sum_{i=1}^{N} (x_i^m \cdot y_i^m)}{\sqrt{\sum_{i=1}^{N} (x_i^m)^2 \cdot \sum_{i=1}^{N} (y_i^m)^2}} \tag{6}$$

Here, the numerator quantifies the overlap of skills between two occupations in terms of the chosen metric (importance or level), and the denominator normalizes the similarity measure to account for variations in the magnitude of skill importance or level. This refined measure ranges from -1, indicating completely dissimilar occupational vectors, to 1, indicating identical vectors. A value of 0 suggests no overlapping skills, highlighting the orthogonal nature of the skill sets. Incorporating this metric enhances our methodology for career transition and workforce development strategies, as it allows for us to account for the response bias of the survey responses when computing skill similarities, considering the chosen aspect of skills (importance or level) across different occupations.

In our approach to calculating a weighted skill similarity, we employ a method that adapts to the specific metric under analysis, whether it be the importance or level of skills, or a combination of both. This adaptability is facilitated through the function $F(m, x, y)$, which determines the appropriate form of cosine similarity to apply. The function is defined as:

$$F(m,x,y) = \begin{cases} \text{Cosine}(m,x,y), & \text{if } m = \text{Importance or Level} \\ \text{Cosine}(\text{Importance},x,y) \cdot \text{Cosine}(\text{Level},x,y), & \text{if } m = \text{Importance and Level} \\ 1, & \text{if } m = \text{Neither} \end{cases} \tag{7}$$

Here, $\text{Cosine}(m, x, y)$ computes the cosine similarity using either the importance or level metrics, based on the value of m. When m is set to 'Importance and Level,' the skill similarity is the product of cosine similarities calculated separately for importance and level, providing a comprehensive view of skill relationships. If neither metric is required, setting m to 'Neither' yields Equation (5). The overall skill similarity between occupations x and y is then given by the equation:

$$\text{Skill Similarity}_{xy} = \left[\frac{1}{|\boldsymbol{Y}|}\sum_{x\in\boldsymbol{X}} \mathbb{1}(x)\right] \cdot F(m,x,y) \cdot 100\% \tag{8}$$

In this equation, $|\boldsymbol{Y}|$ represents the number of unique skills within $\boldsymbol{Y}$. This streamlined formulation allows for a dynamic and efficient analysis of skill similarity, accommodating various analytical needs and perspectives.

4.2 Skill Stock Estimation

The skill stock of labor encapsulates the current status of a regional or national labor market, providing insight into the available skill set and its alignment with market demands. This measure is pivotal in understanding the immediate capacity of the labor force to respond to shifts in occupational demands. To calculate the total labor stock available for each test occupation at a given wage, we employ the following equation:

$$\mathrm{LS}_{y,k}(\theta,\omega) = \sum_{x=1}^{n}\left(\text{Employment}_x \cdot \text{Wage Percentile Met}_x(\omega) \cdot \left[\mathbb{1}\left(\text{Skill Similarity}_x \geq \theta\right)\right]\right), \quad (9)$$

In this equation, $\mathrm{LS}_{y,k}(\theta,\omega)$ represents the labor stock for a specified wage level ω and desired skill similarity threshold θ within region k for a test occupation y. Each existing occupation, indexed by x, contributes to the labor stock based on its employment level, wage percentile alignment, and skill similarity. The indicator function $\mathbb{1}\left(\text{Skill Similarity}_x \geq \theta\right)$ evaluates to 1 when the skill similarity for occupation x meets or exceeds the threshold θ, ensuring that only sufficiently similar skills contribute to the labor stock.

4.3 Skill Flow Estimation

Recognizing that the theoretical labor stock potentially overestimates the actual availability of skill-similar labor, we incorporate observed occupational transitions into our model. This approach provides a more realistic lower-bound estimate of potential labor stock by considering the rates of transition between existing occupations. When conducting our empirical analysis, we focus our attention on this metric as it provides a more comprehensive insight to the potential labor market responses as it incorporates the mobility rates. The skilled-labor flows, derived from the computed skill similarities, are calculated as follows:

$$\begin{aligned}\mathrm{LF}_{y,k}(\theta,\omega) = \sum_{x=1}^{n}\Bigg(&\text{Employment}_x \cdot \text{Mobility Rate}_x \cdot \\ &\text{Wage Percentile Met}_x(\omega) \cdot \left[\mathbb{1}\left(\text{Skill Similarity}_x \geq \theta\right)\right]\Bigg) \quad (10)\end{aligned}$$

where $\mathrm{LF}_{y,k}(\theta,\omega)$ quantifies the labor flow for a desired skill similarity level θ and wage ω in region k for a test occupation y. This sum encompasses all existing occupations (indexed by x), factoring in their employment levels and mobility rates. The mobility rate, Mobility Rate_x, indicates the frequency of transitions out of each occupation, reflecting the dynamic aspect of the labor market. The combined use of wage percentile and skill similarity thresholds provides a comprehensive understanding of labor market dynamics in the context of wage and skill compatibility.

$$\text{Total Flows}_{y,k}(\theta) = \sum_{\forall \omega} \left(\text{LF}_{y,k}(\theta, \omega) \right) \tag{11}$$

This final equation, Total $\text{Flows}_{y,k}(\theta)$, aggregates the labor flows across all wage levels, providing an overall picture of potential labor mobility for the specified skill similarity level within the test occupation in region k. It synthesizes the intricate interplay between skill similarity, wage compatibility, and occupational mobility, offering a comprehensive view of the labor market's responsiveness to evolving skill demands.

5 Empirical Application

In this section, we present our findings, detailing the impact of the CHIPS and Science Act on labor market trends and skill demands within the semiconductor industry. This analysis not only illuminates the immediate effects of the Act but also offers a perspective on the broader implications of industrial policy in high-tech labor markets.

5.1 Industry Background

We consider the salient example of semiconductor manufacturing and the CHIPS and Science Act. The semiconductor industry, pivotal in both global technological advancement and economic strength, presents a compelling case for examining the impact of expansionary industrial policies. Semiconductors, the bedrock of modern electronic devices, are not only central to technological innovation but also crucial to national security. Historically, the U.S. has been a leader in semiconductor innovation, yet it has faced significant challenges in maintaining this position, particularly due to intense competition from East Asian countries in manufacturing capabilities and technological advancements. This competitive landscape has led to substantial policy initiatives in the U.S., most notably the CHIPS and Science Act, aimed at revitalizing the American semiconductor industry (Park, 2023).

The CHIPS and Science Act, a major legislative effort by the U.S. government, signifies a deep commitment to strengthening the domestic semiconductor sector. This Act, with its considerable financial backing, is a strategic move to boost U.S. competitiveness in this essential industry. It reflects a broader global trend where national governments recognize the strategic importance of a robust semiconductor industry for economic security and technological leadership. The global semiconductor market, which reached a record $574.1 billion in 2022, underscores the substantial economic impact of this industry (Semiconductor Industry Association, 2023a).

As we delve into the empirical analysis, our primary focus is on the direct impacts of the CHIPS and Science Act of 2022 on the U.S. semiconductor manufacturing industry. This legislation, which allocates "$52.7 billion for American semiconductor research, development, manufacturing, and workforce development" (House, 2022), marks a critical point for examining shifts in labor dynamics and skill requirements. To provide context for these changes, we begin with a spatial analysis of the semiconductor industry's distribution across the United States, as depicted in Figure 2, utilizing data from the Semiconductor Industry Association (SIA) (Semiconductor Industry Association, 2023b).

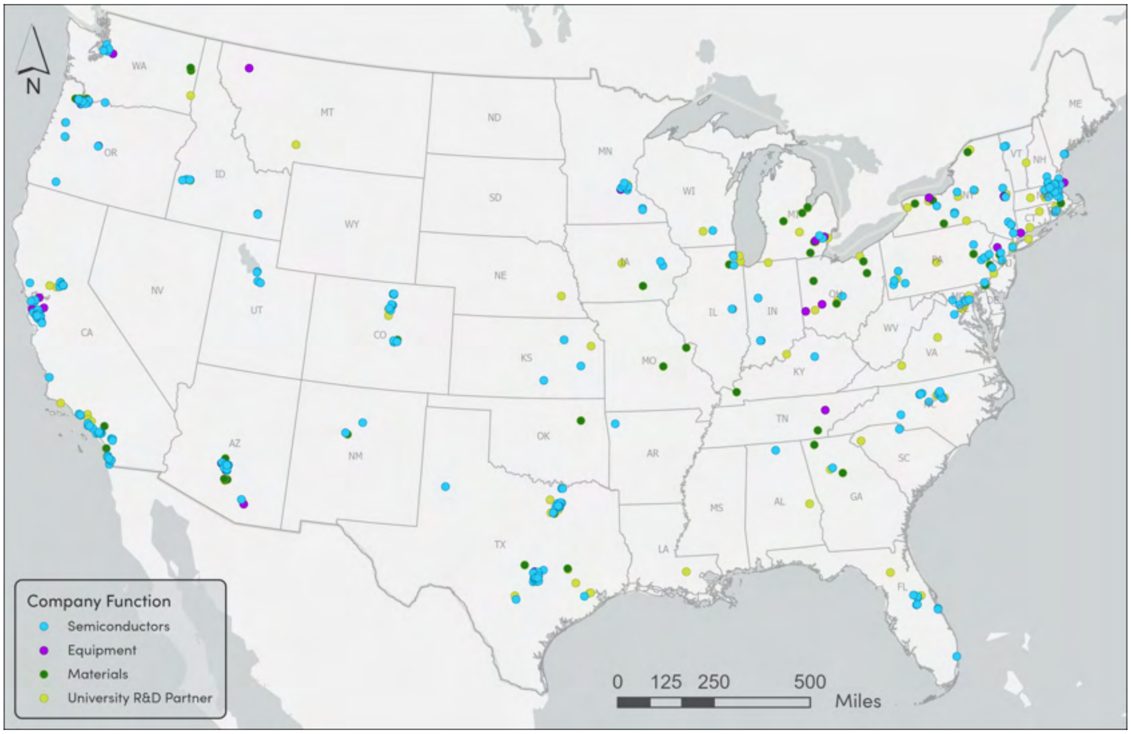


Figure 2: Existing semiconductor-related entities by their function

According to the BLS, the Semiconductor and Other Electronic Component Manufacturing industry (NAICS 334400) employees 176 detailed SOC occupations, ranging from those pertaining to the manufacturing such as Semiconductor Processing Technicians, Computer Hardware Engineers, and Inspectors, Testers, Sorters, Samplers, and Weighers to those involved in the commercial activities such as Light Truck Drivers, Sales Managers, and Lawyers. “Semiconductor Processing Technicians” (SOC code: 51-9141), hereafter referred to as SMPs, represent the second-highest percentage of total employment in the industry at 6.20%.[8] While this may appear inconsequential, the Semiconductor and Other Electronic Component Manufacturing industry accounted for 92.34% of employment for SMPs in 2021 with 22,180 employees out of the total 24,020 in the occupation working in the industry.

[8] The occupation with the highest percent of total employment is “Electrical, Electronic, and Electromechanical Assemblers, Except Coil Winders, Tapers, and Finishers” (SOC code: 51-2028) at 14.13%. The Semiconductor and Other Electronic Component Manufacturing industry accounted for 18.57% of employment for this occupation.

5.2 Skill Profile Construction

This section extends the analytical methods discussed in Sections 4.2 and 4.3 to Semiconductor Processing Technicians (SMPs). Our analysis focuses on how skill similarity variations impact labor acquisition for firms in this sector. Our analytical framework relies on an occupational skill profile, and the choice of profile is critical as it drives the empirical results. For our empirical analysis, we focus our attention on Semiconductor Processing Technicians (SMPs), relying on the O*NET WASK skill profile.[9]

Upon constructing the test occupation skill profile, we estimate the survival function of the skill similarity $S(x)$, defined as the likelihood that the skill similarity score surpasses a specific threshold x. This is expressed mathematically as:

$$S(x) = 1 - F(x) \tag{12}$$

where $F(x)$ represents the cumulative distribution function of skill similarities across occupations. To integrate the variable of employment into our analysis, we modify the survival function to include weights, w_i, proportional to the employment figures for each occupation. This adaptation yields a weighted survival function, $S_w(x)$, which is formulated as follows:

$$S_w(x) = \frac{\sum_{i=1}^{n} w_i \cdot \mathbb{1}_{\{X_i > x\}}}{\sum_{i=1}^{n} w_i} \tag{13}$$

In this equation, X_i denotes the skill similarity score for occupation i, and $\mathbb{1}_{\{X_i > x\}}$ is an indicator function that evaluates to 1 when X_i exceeds x, otherwise 0. This approach allows us to more

[9] The skill profiles provided by O*NET provide a baseline estimation of the skills necessary for successful employment for a given occupation, but are limited due to the all-encompassing nature of the WASK items. We conduct a sensitivity analysis of semiconductor-manufacturing related occupations based on expert elicited profile characteristics in the Supplementary Materials.

accurately reflect the distribution of skill similarities, considering the significance of each occupation based on its workforce size. The results of this weighted survival function are presented in Figure 3 and include the distribution of skill similarities in the context of employment size.

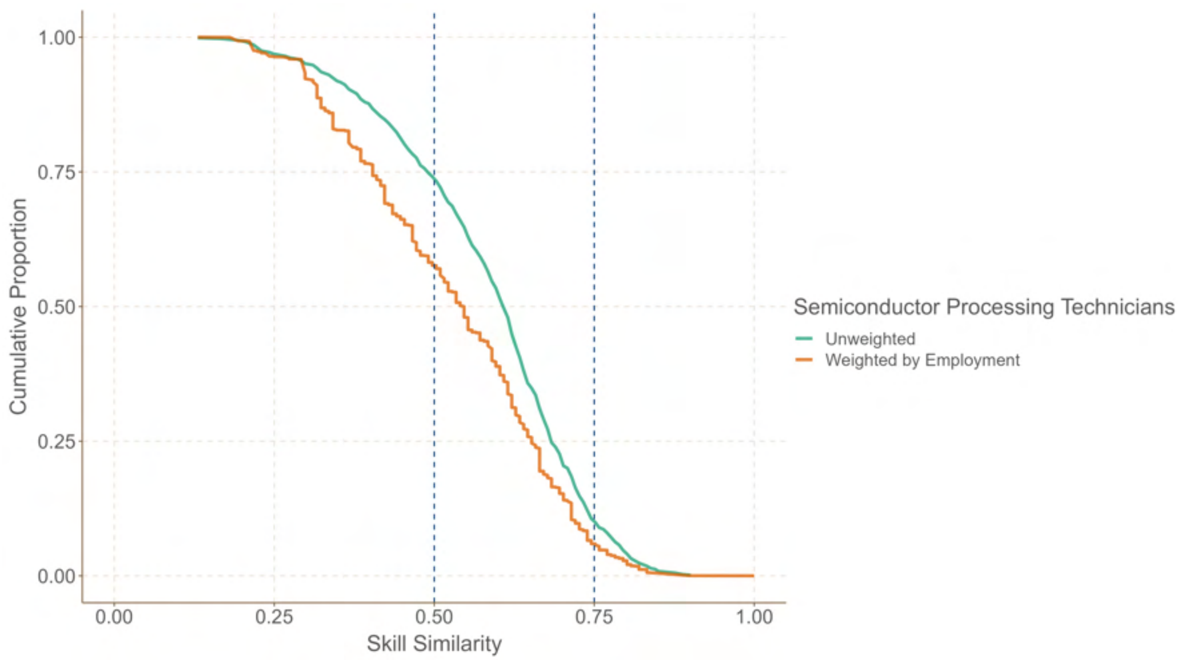


Figure 3: Survival functions of Semiconductor Processing Technicians (cosine similarity-weighted with mean-based similarity computation). The two curves depict the survival function based on the distribution of occupations and the distribution of occupations weighted by the employment in those occupations.

The survival function in Figure 3 has a steep slope for both the unweighted and employment-weighted computations. This indicates that there are skills that are likely to be specific to the technical expertise necessary for SMPs. When we incorporate the employment-based weighting for the survival function computation, we see that the occupations that meet the 50% and 75% skill similarity levels have fewer employees, which highlights the scarcity of available talent based on the skill profile considered.

5.3 Supply Stock and Flow Estimation

We incorporate the skill similarities above to estimate the supply stock and flows of SMPs-skill-similar regional labor. To ground our discussion, we present the distribution of the jobs announced from the CHIPS and Science Act funding by depicting the corresponding quantities of jobs created in Figure 4. In total, 43,580 jobs have been created based on the funding distributed to the Semiconductors & Electronics industry. The map presents the number of jobs created across the various MSAs that received funding (The White House, 2023). The map also highlights the four MSAs of interest we identified, based on the numbers of jobs created: Syracuse, NY, Phoenix-Mesa-Scottsdale, AZ, Sherman-Denison, TX, and Columbus, OH.

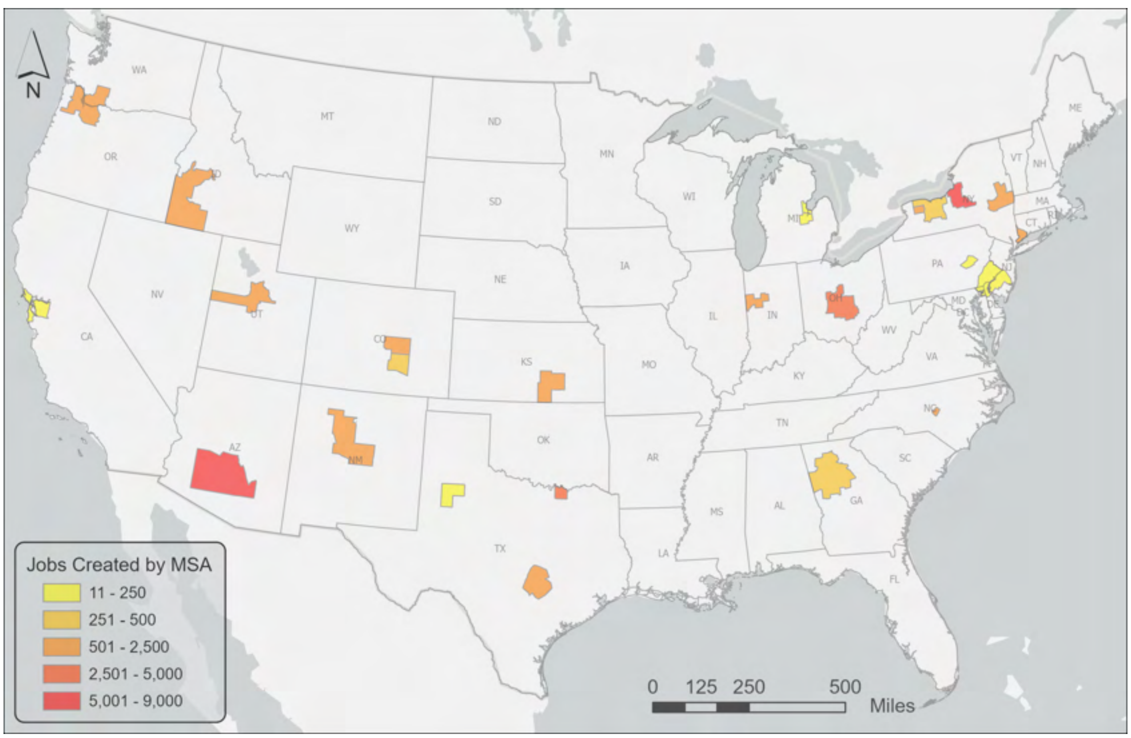
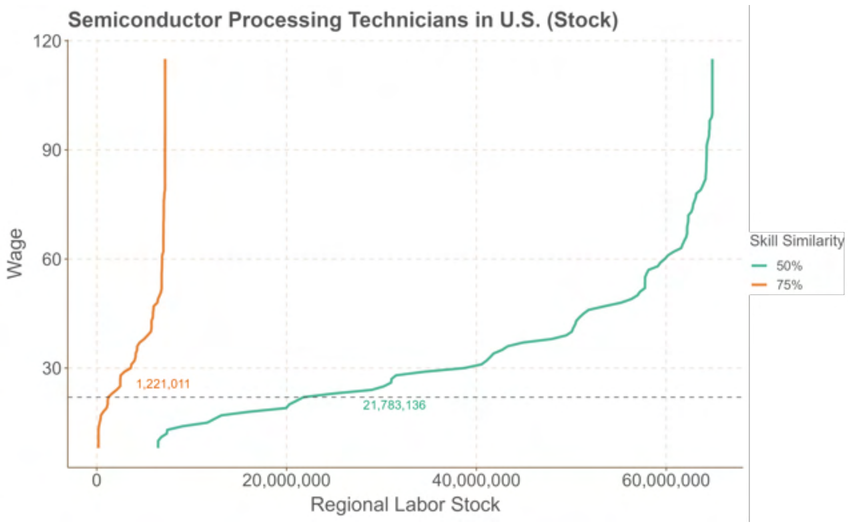
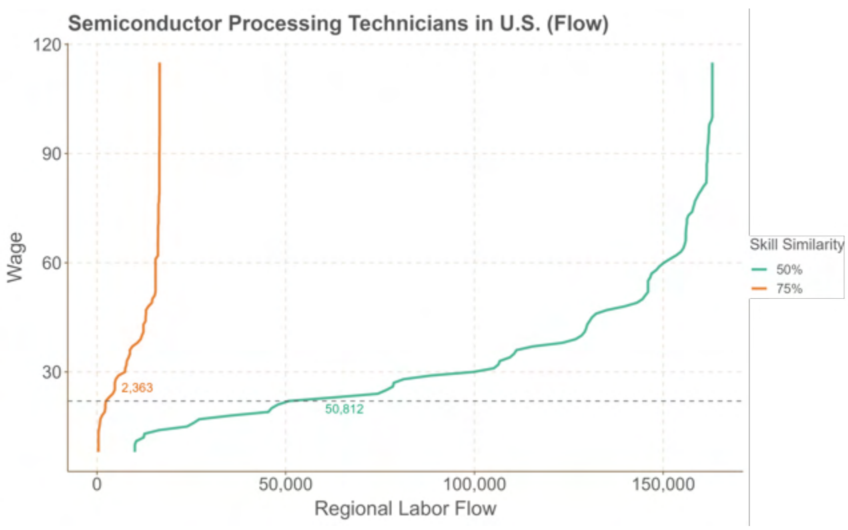


Figure 4: Announced Job creation in semiconductors and electronics by MSA, as of October 5th, 2023

We apply Equations 9 and 10 to compute the national and regional potential labor stock and flow levels for SMPs. We begin by considering the case of the national labor market estimates. Figure 5 presents the results for the labor stock and flow at the national level. We also provide the national labor stock of SMPs to ground our discussion. In Figures 5a and 5b we see that reducing the skill similarity parameter increases the size and changes the composition of the available skill-similar labor pool, with lower skill similarity thresholds yielding larger potential labor pools. From the figures, we see that when the criteria for skill similarity is lowered from 75% to 50%, both the stock and flow of labor increase, highlighting the potential benefits of training workers from closely related occupations.



(a) National labor stock curves



(b) National labor flow curves

Figure 5: National labor curves for Semiconductor Processing Technicians given 50% and 75% skill similarity (mean-based similarity computation)

If we maintain the 6.20% employment rate of SMPs within the semiconductor manufacturing industry, then, of the 43,580 jobs created, approximately 2,702 would be SMPs. Based on our results, at a national level, the labor demand increase could potentially be met at a skill similarity threshold below 75%, which may not be viable given the technical nature of the position. While these results consider the skill-similar labor pool, a consideration of the existing labor stock of those employed in the occupation is also of interest, as workers employed as SMPs provide an immediate source for recruitment for new SMPs. We present the national existing labor stock as depicted in Figure 6, which captures the wage distribution and stock of employment, with $22 as the wage corresponding to the intersected value.

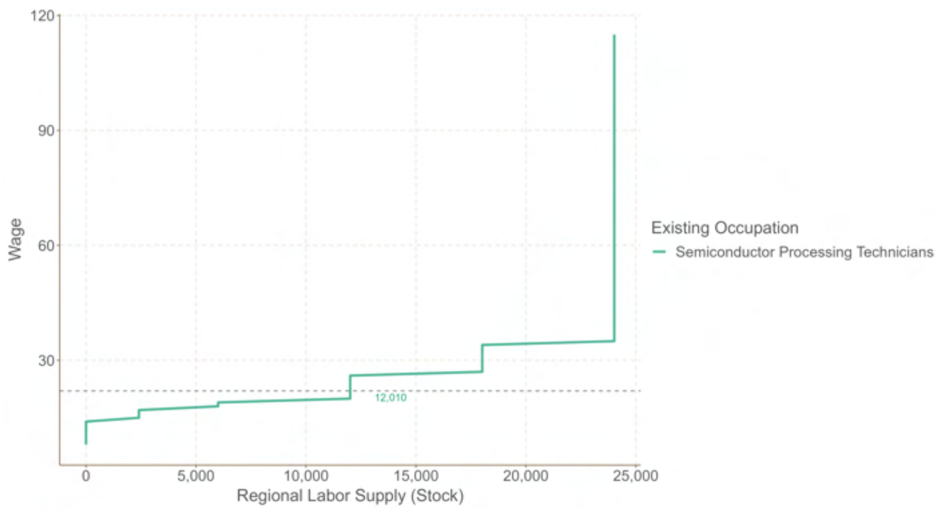


Figure 6: National labor stock curve of workers employed as Semiconductor Processing Technicians in 2021

The aggregate of the existing SMPs and skill-similar-occupation employed workers labor flows suggests that finding workers to meet the labor demand shocks may be feasible, but there are potential limitations to consider. First, while we have this potential labor flow at a national level, this does not imply that the needs of the MSA-specific labor demand shocks that arise due to the influx of funding can be met by the regional labor composition as the distribution of employment in those occupations is not uniform across MSAs. Second, the feasibility of recruiting all workers within skill-similar occupations is limited, as it would be unreasonable to deplete those occupations within an MSA. Third, this implication overlooks the likelihood of successful recruitment from those existing occupations by not incorporating wages into the consideration.

To underscore the spatial variations in the existing employment of SMPs, we present the employment and wage distributions of SMPs by MSA and nationally for 2021 in Table 1. The national existing supply of SMP employees across all wage levels is 24,020. From the Table, we see that there are substantial variations in the employment levels of SMPs across MSAs, with employment ranging from 60 workers in Santa Maria-Santa Barbara, CA to 4,640 works employed in Portland-Vancouver, Hillsboro, OR-WA. We also see that wage distributions vary substantially across MSAs ranging from a median hourly wage of $14.34 in Houston-The Woodlands-Sugar Land, TX to $29.19 in Boston-Cambridge-Nashua, MA-NH. The variation in the distribution of employment and wages across MSAs presents additional complexities to consider when we consider the distribution of potential employment. These variations in regional labor flows and wage distributions highlight the importance of spatial considerations for funding allocation decisions as well as recruitment efforts, and demonstrate that the national levels of potential labor do not directly correlate to regional labor.

Table 1: Semiconductor Processing Technicians employment and wage distributions by location (2021)

Location	Employment	Location Quotient	Hourly Wage					
			Mean	10th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	90th Pctl.
Albuquerque, NM	610	9.79	$23.33	$14.51	$14.56	$ 18.32	$28.96	$45.80
Allentown-Bethlehem-Easton, PA-NJ	170	2.87	$19.34	$17.48	$17.48	$ 17.53	$18.09	$22.81
Boise City, ID	500	8.67	$17.92	$13.02	$14.49	$ 17.48	$20.24	$27.27
Dallas-Fort Worth-Arlington, TX	2,120	3.46	$16.88	$11.90	$13.46	$ 17.37	$17.57	$20.58
Houston-The Woodlands-Sugar Land, TX	180	0.37	$14.96	$11.24	$11.24	$ 14.34	$18.13	$18.13
Los Angeles-Long Beach-Anaheim, CA	1,230	1.26	$20.23	$14.44	$17.59	$ 18.18	$22.52	$28.01
Minneapolis-St. Paul-Bloomington, MN-WI	250	0.82	$19.17	$14.55	$14.55	$ 18.27	$23.12	$23.12
New York-Newark-Jersey City, NY-NJ-PA	470	0.32	$24.28	$17.59	$19.70	$ 22.22	$28.19	$35.71
Orlando-Kissimmee-Sanford, FL	70	0.33	$19.94	$14.46	$14.46	$ 18.45	$23.38	$29.49
Oxnard-Thousand Oaks-Ventura, CA	180	3.49	$23.50	$14.74	$14.98	$ 18.98	$27.61	$37.14
Phoenix-Mesa-Scottsdale, AZ	2,200	6.10	$27.96	$18.13	$18.49	$ 28.96	$36.73	$36.99
Portland-Vancouver-Hillsboro, OR-WA	4,640	24.26	$24.63	$18.16	$18.55	$ 23.10	$28.19	$35.71
San Diego-Carlsbad, CA	340	1.44	$25.62	$15.08	$17.59	$ 19.17	$28.77	$47.53
San Francisco-Oakland-Hayward, CA	290	0.75	$24.91	$17.14	$20.45	$ 25.06	$29.19	$33.28
San Jose-Sunnyvale-Santa Clara, CA	2,450	13.47	$25.07	$17.90	$18.26	$ 22.55	$28.75	$36.01
Santa Maria-Santa Barbara, CA	60	1.78	$27.20	$17.87	$22.04	$ 27.97	$28.96	$35.43
Sherman-Denison, TX	360	44.25	$15.91	$11.56	$14.27	$ 14.45	$18.08	$18.12
Boston-Cambridge-Nashua, MA-NH	580	1.31	$28.10	$23.18	$23.20	$ 29.19	$29.57	$36.64
National	24,020	-	$22.07	$14.34	$17.35	$ 19.17	$26.88	$34.74

Source: OEWS (2021)

We now consider the spatial variations in the skill-similar potential labor pool by considering the four MSAs with the greatest numbers of jobs announced based on funding from the CHIPS and Science Act. Figure 7 depicts the computed regional labor flows; we include the numbers of jobs announced for each MSA to provide context to the estimated labor availability at the test wages. We use a test wage of $22 as this was the national mean wage for SMPs. Note that the gaps between the different skill similarity thresholds vary by MSA. Even if we assume a maintained 6.20% of the industry's employment is in SMPs, the labor flows do not meet the needs of the employment announced. For instance, the local labor market in Phoenix-Mesa-Scottsdale, AZ has a theoretical capability to meet the labor demands, but only when we reduce the skill similarity threshold to 50%.[10] Expanding hiring pools by reducing minimum skill thresholds from 75% to 50% substantially increases the number of potentially available workers in certain MSAs, however, simply having more candidates does not guarantee better outcomes, as costs associated with training and workforce development of candidates with reduced skill-profile overlap may be significant.

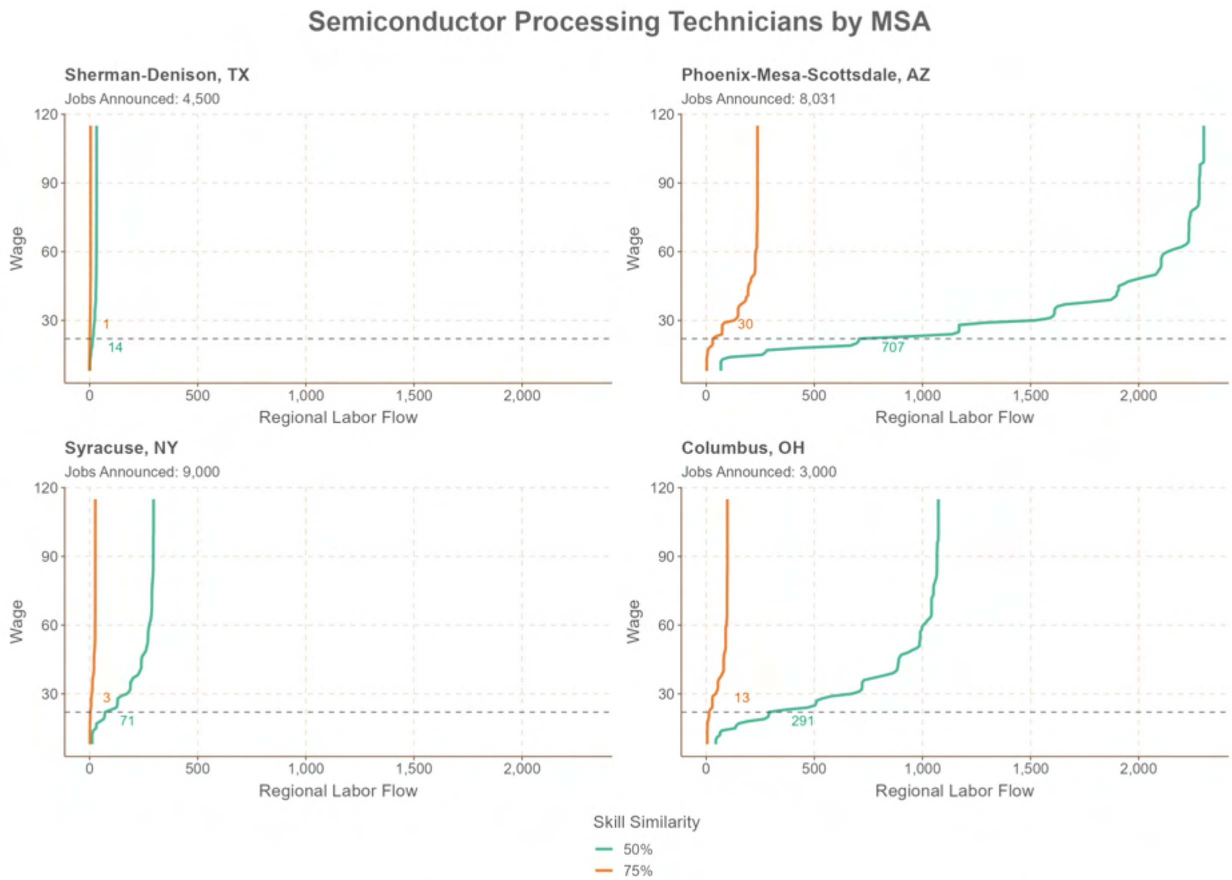


Figure 7: Labor flow curves for Semiconductor Processing Technicians for each MSA of interest given 50% and 75% skill similarity (mean-based similarity computation). Intersect values are computed at the approximate national mean wage of $22.

Figure 7 illustrates that the distribution of manufacturing jobs created by the CHIPS and Science Act does not directly align with the distribution of potential SMP labor flows of SMPs. For

[10] This assumption is based on the 8,031 jobs created corresponding to an approximate 44 SMP positions being created, based on the 6.20% industry employment ratio.

instance, Columbus, OH has significant SMP talent flow availability yet relatively low announced job growth under the Act, whereas investment in Sherman-Denison, TX with more limited SMP pools may struggle to catalyze industry expansion. This potential mismatch between funding and extant skill reservoirs indicates suboptimal targeting given labor constraints.

As discussed, the potential for the influx of labor demanded to be met is not captured solely by the labor stocks and flows we estimate. Considerations of the wage distributions and regional wage variations are critical for identifying the effective potential labor pool for recruitment. Returning to the national framework, we may consider the ten occupations with the highest skill similarity values, which are presented in Table 2. In addition to the variety of job titles that have high skill similarity to SMPs, the results highlight the substantial national-level variation in wage and employment levels across occupations that have similar WASK profiles to SMPs. Though these occupations have relatively similar skill similarity values to SMPs, which range from 71.4% to 86.4%, the associated wage distributions exhibit considerable variation. For example, the median wage of Computer Numerically Controlled Tool Operators was \$22.42 and \$39.62 for Ship Engineers; the substantial difference in wages highlights the limitations of focusing the consideration on skill similarity, as we cannot reasonably argue that the opportunities to recruit from these two example occupations are equivalent.

Table 2: Top 10 occupations most skill-similar to Semiconductor Processing Technicians and their national wage distributions

Job Title	Skill Similarity	Employment	Hourly Wage					
			Mean	10th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	90th Pctl.
Captains, Mates, and Pilots of Water Vessels	0.864	33,490	$47.27	$17.91	$28.56	$39.25	$58.90	$76.77
Computer Numerically Controlled Tool Operators	0.790	157,840	$22.23	$14.53	$18.03	$22.42	$24.34	$29.73
Aircraft Cargo Handling Supervisors	0.758	8,590	$29.84	$18.67	$23.17	$25.74	$38.38	$39.64
Commercial Pilots	0.758	42,770	-	-		-	-	-
Gas Compressor and Gas Pumping Station Operators	0.753	2,910	$32.27	$18.51	$23.75	$34.00	$38.70	$43.63
Ship Engineers	0.743	7,650	$46.59	$23.76	$30.93	$39.62	$50.92	$67.02
Rail Yard Engineers, Dinkey Operators, and Hostlers	0.735	4,460	$27.92	$18.53	$22.77	$29.37	$31.01	$38.11
Pump Operators, Except Wellhead Pumpers	0.728	10,600	$26.15	$16.41	$18.67	$23.84	$31.12	$38.38
Sailors and Marine Oilers	0.723	26,610	$27.79	$14.00	$17.01	$22.46	$29.53	$37.67
Airline Pilots, Copilots, and Flight Engineers	0.714	81,310	-	-	-	-	-	-

5.4 Relationship between Skill Similarity and Occupational Transitions

The exploration of the relationship between skill similarity and occupational transitions is a critical aspect of our analysis, focusing on validating the potential of skill similarity as a measure of labor market potential. This section of the study employs both Ordinary Least Squares (OLS) and Beta regression models to comprehensively examine this relationship. The OLS model, as expressed in Equation (14), serves as the foundational model:

$$\text{Transition}_{ij} = \beta_0 + \beta_1 \cdot \text{Skill Similarity}_{ij} + \beta_2 \cdot \text{RD}^{\omega}_{ij} + \beta_3 \cdot \text{RD}^{\lambda}_{ij} + \varepsilon_{ij} \tag{14}$$

where $\text{RD}^{\omega}_{ij} = \frac{\omega_j - \omega_i}{\omega_j + \omega_i}$ computes the relative wage difference, and $\text{RD}^{\lambda}_{ij} = \frac{\lambda_j - \lambda_i}{\lambda_j + \lambda_i}$ is the relative employment difference.

In this fullest form of our baseline model, the dependent variable, Transition_{ij}, quantifies the likelihood of a worker transitioning from occupation i to occupation j, where $i = j$ cases are included. This model posits that the transition probability is influenced by several key factors: the skill similarity between the two occupations (Skill Similarity$_{ij}$), the relative wage difference ($\mathrm{RD}^{\omega}_{ij}$), and the relative employment difference ($\mathrm{RD}^{\lambda}_{ij}$). Specifically, β_1 measures the extent to which skill similarity between origin and destination occupations impacts the transition probability. Similarly, β_2 and β_3 capture the effects of relative differences in wages and employment, respectively, on occupational transitions. The term ε_{ij} represents the error term, encapsulating unobserved factors that may influence these transitions. The empirical results are presented in Table 3 below.

Table 3: OLS Regression Estimates

	Dependent variable:		
	Occupational Transition Rates		
	(1)	(2)	(3)
Skill Similarity	0.45^{***}	0.29^{***}	0.45^{***}
	(0.01)	(0.01)	(0.01)
Relative Mean Wage Difference	0.22^{***}		0.22^{***}
	(0.01)		(0.01)
Relative Employment Difference		-0.01^{***}	-0.00
		(0.00)	(0.00)
Constant	-0.21^{***}	-0.13^{***}	-0.21^{***}
	(0.00)	(0.00)	(0.00)
R^2	0.25	0.16	0.25
Observations	10,794	10,958	10,794

Note: *p<0.1; **p<0.05; ***p<0.01

The OLS regression results presented in Table 3 offer insightful interpretations into the relationship between occupational transitions, skill similarity, wage differences, and employment differences. The consistently positive and significant coefficient of skill similarity across all three columns (0.45, 0.29, and 0.45 with $p < 0.001$) strongly suggests that greater similarity in skills between two occupations increases the likelihood of a worker transitioning between these occupations. This finding aligns with the intuitive understanding that similar skill sets facilitate smoother occupational shifts, reducing the costs and barriers associated with acquiring new skills. Notably, the coefficient is robust across different column specifications, reinforcing the reliability of this result.

The coefficients for the relative mean wage difference (0.22 in columns 1 and 3, significant at $p < 0.001$) indicate that wage differentials are a significant predictor of occupational transitions, with higher wage differences correlating with increased transition rates. This relationship underscores the economic motivation behind occupational changes, where wage incentives play a pivotal role. The relative employment difference, however, exhibits a less consistent pattern. Its coefficient is significant and negative in column 2 (-0.01, $p < 0.001$), suggesting that greater employment disparities between occupations might slightly deter transitions. However, this effect is not significant in the comprehensive model (column 3), indicating that its impact might be more nuanced or overshadowed by other factors such as skill similarity and wage differences.

The standard errors associated with these coefficients are relatively small (ranging from 0.00 to 0.01), indicating a high level of precision in the estimates. This precision lends further credibility to the findings, suggesting that the observed effects are not products of random variation but reflect underlying patterns in occupational transitions. The R-squared values, ranging from 0.16 to 0.25, while not exceedingly high, do indicate that a reasonable proportion of the variance in occupational transition rates is explained by the model. This suggests that while the included variables are significant predictors, other factors not captured in the model also play a role in determining occupational transitions.

It is crucial to note the inherent limitations of the OLS approach in this context, particularly concerning the assumptions of normality and homoskedasticity. Given that the dependent variable, occupational transition rates, is a probability measure bound between 0 and 1, the OLS model risks violating these assumptions. This can lead to issues such as biased estimates and predictions that fall outside the logical range of probabilities. Moreover, the linear framework of OLS may not adequately capture the nuanced relationships in data where the dependent variable is bounded, as is the case with probabilities. These limitations necessitate the transition to a Beta regression model, as discussed in the subsequent section of the paper, to provide a more accurate and theoretically appropriate analysis of the data. The Beta regression model's ability to accommodate the unique characteristics of probability data, such as skewness and heteroscedasticity, and to keep predictions within the 0 to 1 range, ensures a more realistic and reliable interpretation of the transition probabilities.

In transitioning from the OLS model to Beta regression, our analysis addresses several inherent limitations of the OLS framework, particularly when dealing with probability measures like our dependent variable, Transition_{ij}. The OLS model, while providing valuable initial insights, is constrained by its assumptions of normality and homoskedasticity, assumptions that are often not tenable with bounded dependent variables such as probabilities. This deficiency is further compounded by the linear nature of OLS, which can lead to implausible predictions outside the 0 to 1 range for probabilities.

Beta regression, tailored for bounded dependent variables, effectively mitigates these issues by accommodating the skewness and heteroskedasticity often present in probability data. This methodological shift allows for the variance of the dependent variable to be modeled as a function of its mean, enhancing the flexibility and accuracy of our analysis. Importantly, the structure of Beta regression is more congruent with the characteristics of our data, ensuring that the model's predictions are confined within the realistic bounds of 0 to 1. This alignment results in a more accurate and practical interpretation of occupational transition probabilities, reflecting the nuanced realities of labor market dynamics. Our approach to Beta regression is operationalized in the equations that follow, providing a detailed framework for this more sophisticated modeling technique.

$$\log\left(\frac{\mu_{ij}}{1-\mu_{ij}}\right) = \beta_0 + \beta_1 \cdot \text{Skill Similarity}_{ij} + \beta_2 \cdot \text{RD}^{\omega}_{ij} + \beta_3 \cdot \text{RD}^{\lambda}_{ij}, \tag{15}$$

$$\text{Transition}_{ij} \sim \text{Beta}(\mu_{ij}, \varphi_{ij}), \tag{16}$$

$$\log(\varphi_{ij}) = \gamma_0 + \gamma_1 \cdot \text{Occ. Change}_{ij}. \tag{17}$$

Equation (15) estimates the logit of the mean of the transition probability, μ_{ij}, as a function of skill similarity, relative wage difference (RD^{ω}_{ij}), and relative employment difference (RD^{λ}_{ij}). The coefficients β_1, β_2, and β_3 measure the impact of these respective factors on the log odds of occupational transition probabilities. Equation (16) establishes that the transition probabilities follow a beta distribution, characterized by the mean μ_{ij} and the precision parameter φ_{ij}. Equation (17) models the log of the precision parameter as a function of the occupational change indicator, Occ. Change_{ij}. The γ_1 term quantifies the effect of occupational change on the variance of the transition probabilities.

Table 4: Beta Regression Estimates

	Dependent variable:			
	Occupational Transition Rates			
	(1)	(2)	(3)	(4)
Skill Similarity	1.54***	0.71***	1.49***	0.58***
	(0.06)	(0.05)	(0.06)	(0.06)
Relative Mean Wage Difference	0.66***		0.76***	0.45***
	(0.05)		(0.05)	(0.04)
Relative Employment Difference		0.22***	0.24***	0.66***
		(0.02)	(0.02)	(0.01)
Constant	−3.63***	−3.18***	−3.62***	−5.95***
	(0.04)	(0.03)	(0.04)	(0.03)
Precision:				
φ	3.58***	3.56***	3.66***	
	(0.07)	(0.07)	(0.07)	
Constant				−0.75***
				(0.06)
Occupational Change Dummy				6.06***
				(0.06)
Pseudo R^2	0.16	0.25	0.29	0.24
Log-Likelihood	40,030.44	40,649.75	40,157.10	48,931.58
Observations	10,794	10,958	10,794	10,794

Note: *p<0.1; **p<0.05; ***p<0.01

The Beta regression results, detailed in Table 4, deepen our understanding of the factors influencing occupational transitions, showcasing how various predictors interact within the confines of a probability framework. Notably, the coefficients for skill similarity, presented in log-odds format, reveal a significant and variable impact across the models. For instance, in column 1, the coefficient of 1.54 ($p < 0.01$) indicates that a one-unit increase in skill similarity substantially increases the log-odds of transitioning between occupations. However, this effect is moderated in the subsequent models - 0.71 in column 2, 1.49 in column 3, and 0.58 in the comprehensive column 4 - highlighting the influence of other factors like wage and employment differences when they are included in the analysis.

The coefficients for the relative mean wage difference and relative employment difference in columns 1, 3, and 4 demonstrate that these economic factors significantly affect the transition probabilities. The log-odds increase by 0.66 to 0.76 for the wage difference and 0.22 to 0.66 for the employment difference (all significant at $p < 0.01$) with a one-unit increase in these predictors. This suggests that both wage and employment differentials have a more pronounced effect on occupational transitions than what was observed in the OLS models. The larger magnitude of these coefficients in the Beta regression context, compared to the OLS results, underscores the importance of modeling these relationships within an appropriate statistical framework for probability measures.

Model 4, which includes all predictors, provides a comprehensive view, showing how each factor independently and collectively influences occupational transitions. The diminished coefficient for skill similarity in this model (0.58, $p < 0.01$) compared to the others suggests that its effect is less dominant when wage and employment differences are accounted for. This result implies a complex interplay among these variables, where the influence of skill similarity is significant but moderated in the presence of economic factors.

The inclusion of the precision parameter in the Beta regression, particularly in column 4, is a significant advancement over the OLS model. The large coefficient for the occupational change dummy (6.06, $p < 0.01$) indicates a considerable variation in the dispersion of transition probabilities. This finding suggests that occupational transitions are more heterogeneous than what could be captured by the OLS model, highlighting the importance of using a more flexible approach like Beta regression for such bounded probability data.

The Beta regression analysis provides a richer and more accurate portrayal of the determinants of occupational transitions. By addressing the limitations of the OLS model, particularly in terms of handling bounded, non-linear relationships and accommodating variability in data, Beta regression offers a more nuanced understanding of how skill similarity, wage, and employment differences interact to influence occupational transitions. These insights are invaluable for policymakers and researchers interested in the dynamics of labor market mobility, as they provide a clearer picture of the factors that drive occupational changes.

5.5 Comparative Wage Position

In Figure 6, we identify that reliance on existing SMPs or transition pathways into SMPs to address this labor demand shock would not adequately address the quantity of labor demanded, even when removing spatial distributions of labor as a consideration. The dearth of potential labor availability within SMPs warrants the analysis of available labor beyond those employed as SMPs. Figure 7 highlights that increases in demand caused by the creation of new jobs will not expressly be satisfied by skill similar occupations; though we find that some MSAs could theoretically handle the influx of labor demand. This consideration, however, does not incorporate the variations in wage distributions and competitiveness that will play a significant role in the ability for entities to recruit workers within an MSA of interest.

We integrate the dimensions of skill-similar occupations and wage distributions through the lens of regional wage competitiveness. This approach enables us to pinpoint regions that align closely with the national wage distribution trends for Semiconductor Processing Technicians (SMPs), thereby identifying areas with optimal wage efficiency for these roles. Integrating the relationship between wages and skill similar labor across different regions enables policymakers and industry stakeholders to develop more effective strategies for workforce development and economic planning.

We analyze the comparative wage position of SMPs relative to occupations with similar skill sets, considering the 50% and 75% skill similarity levels. The methodology employs a detailed percentile-based wage analysis within the SMP occupational category, contrasting these with similar professions. We begin by identifying the wage at each percentile for SMPs, denoted as $W_{SMP,i}$ for the i^{th} percentile. These wages are subsequently compared to those in skill-comparable occupations. For each existing occupation o deemed comparable, we compute the lowest percentile, $P_{o,i}$, where the wage equals or surpasses $W_{SMP,i}$. This relationship is computed as

$$P_{o,i} = \min\{p : W_{o,p} \geq W_{SMP,i}\}, \tag{18}$$

where $W_{o,p}$ represents the wage at the p^{th} percentile for occupation o.

Following this, we calculate the proportion of the wage distribution for each SMP wage bin that aligns with or exceeds the wages in comparable occupations. This proportion, represented as R_i, is derived as the average of the minimum wage percentiles $P_{o,i}$ across all comparable occupations, calculated as

$$R_i = \frac{1}{N} \sum_{o=1}^{N} P_{o,i}, \tag{19}$$

where N indicates the number of comparable occupations. An aggregate share A_i for each bin is then computed. This is achieved by multiplying the proportion R_i by the number of SMP workers in that wage bin ($N_{SMP,i}$), thereby yielding

$$A_i = R_i \cdot N_{SMP,i}. \tag{20}$$

This calculation weights the competitiveness of each wage bin by its share of workers.

The final phase of the analysis consolidates these individual bin scores to compute an overall competitiveness score C, which is the average of these weighted aggregate shares across all bins. This is expressed as

$$C = \sum_i A_i. \tag{21}$$

The score C encapsulates the comprehensive competitiveness of SMP wages in comparison to similar occupations. This analytical approach offers valuable insights into the wage dynamics in the labor market, especially for occupations like SMPs. It provides a lens through which wage competitiveness across different wage levels relative to similar occupations can be understood, contributing significantly to the discourse on wage structures and labor market dynamics.

Figures 8 and 9 present the wage competitiveness estimates based on the MSA-specific wage distributions for SMPs relative to the national levels based on the 50% and 75% skill similar existing occupations, respectively.

Figure 8: Wage competitiveness of 50% skill similar occupations in 2021. National wage competitiveness: 63.6%

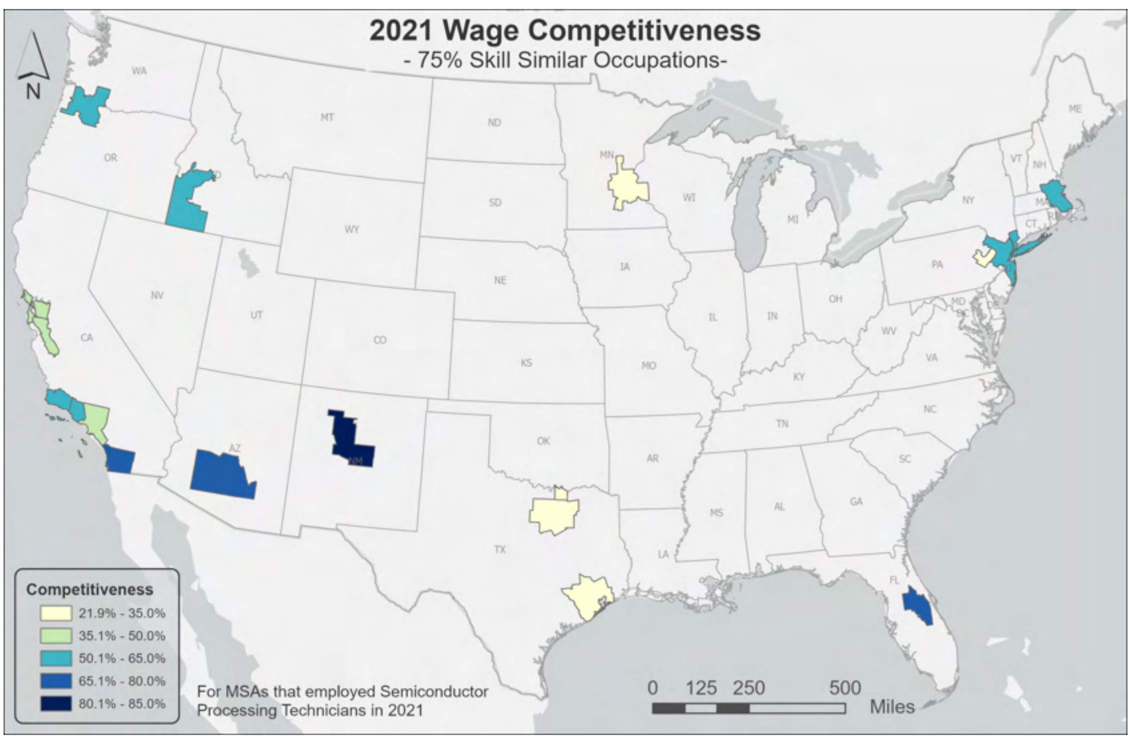


Figure 9: Wage competitiveness of 75% skill similar occupations in 2021. National wage competitiveness: 69.0%

5.6 Opportunities for Training Employment?

In Sections 5.3 and 5.5, we discussed the limitations of reliance on existing labor stocks and the need to incorporate wage variations to anchor the implications of the skill-similarity-based potential labor stocks and flows. Beyond these considerations, we may consider the base possibility that some local labor markets may not have sufficiently skill-similar labor to meet the requirements of the labor demand shocks. We can identify opportunities for training in skills. In particular, we can identify skills that have low levels of satisfaction, which here means that the necessary skill level is met. Knowledge of the skills that would result in improvements of skill capabilities is important and provides policy-makers with opportunities for targeted policy. The computation of average skill satisfaction for each skill involves aggregating individual satisfaction values across all occupations. This is formalized in the equation:

$$S_i = \frac{1}{N} \sum_{x=1}^{N} \mathbb{1}(x) \tag{22}$$

where S_i represents the average skill satisfaction for skill i, N is the number of occupations compared, and $\mathbb{1}(x)$ is the satisfaction indicator function as defined in Equation (3) or (4), depending on the chosen certainty approach. When incorporating cosine similarity weighting for skill importance or level, this computation is adjusted to reflect a weighted average skill satisfaction:

$$S_i^w = \frac{1}{N} \sum_{x=1}^{N} \mathbb{1}(x) \cdot W_i^x \tag{23}$$

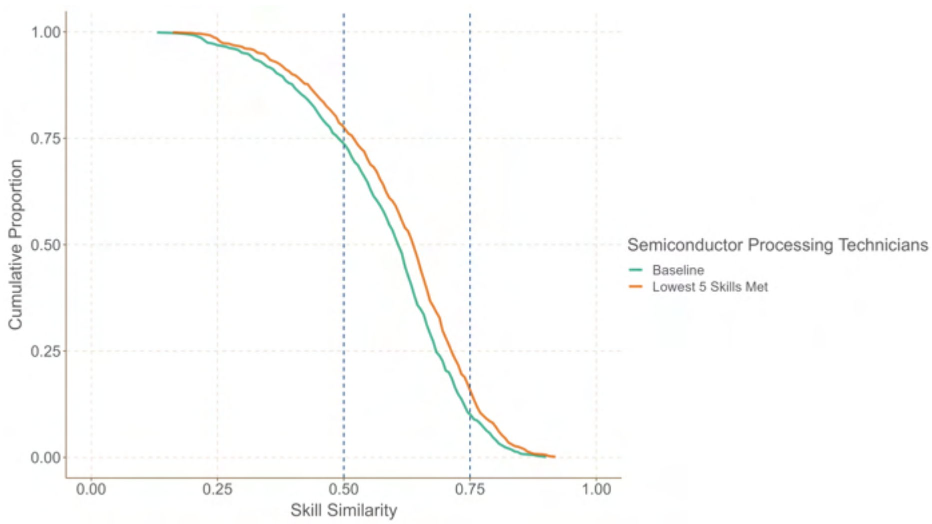
In this weighted version, W_i^x denotes the cosine similarity weight for skill i in occupation x. We applied this estimation approach to SMPs. In Table 5, we present the 15 skills with the lowest average skill satisfaction and the 15 skills with the highest.

Table 5: Average skill satisfaction by existing occupations for the 15 skills with the lowest and highest levels of skill satisfaction, based on levels required by Semiconductor Processing Technicians

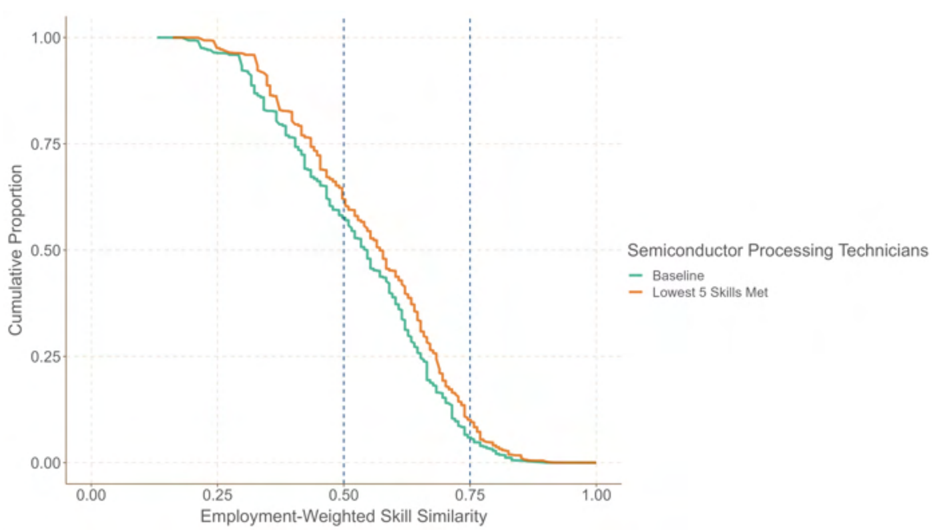
Domain	Skill	Satisfaction
A	Finger Dexterity	0.07
S	Quality Control Analysis	0.09
K	Production and Processing	0.11
A	Arm-Hand Steadiness	0.12
S	Operations Monitoring	0.12
W	Controlling Machines and Processes	0.12
A	Perceptual Speed	0.13
S	Equipment Maintenance	0.15
A	Response Orientation	0.15
W	Repairing and Maintaining Electronic Equipment	0.15
K	Chemistry	0.17
A	Manual Dexterity	0.18
S	Repairing	0.19
A	Rate Control	0.19
W	Inspecting Equipment, Structures, or Materials	0.21
⋮	⋮	⋮
W	Performing Administrative Activities	0.91
S	Management of Personnel Resources	0.92
K	Administrative	0.92
K	History and Archeology	0.92
A	Speed of Closure	0.93
W	Communicating with People Outside the Organization	0.95
K	Psychology	0.95
K	Transportation	0.95
K	Geography	0.97
K	Personnel and Human Resources	0.97
K	Economics and Accounting	0.97
K	Sales and Marketing	0.98
K	Law and Government	0.98
A	Dynamic Flexibility	1.00
A	Explosive Strength	1.00

† denotes soft-skills as identified by O*NET.

This diagnostic assessment extends beyond superficial matches to signal areas of overlapping or complementary skill deficiencies. Workforce training programs that target such clusters of correlated skills would likely contribute to more efficient and effective labor market outcomes. Figures 10a and 10b substantiates this through simulated market shifts, simulating the case where the top five most significant skill gaps are addressed across associated occupations.



(a) Survival functions based on the number of occupations.



(b) Survival functions weighted by the number of employees in the corresponding existing occupations.

Figure 10: Survival function response to having the five lowest skills by satisfaction met by all existing occupations.

The significant upward shifts seen in the survival function curves in Figures 10a and 10b highlight the substantive potential to expand the pool of viable talent for targeted occupations by addressing select skill gaps among workers in occupations with relevant skill profiles. Targeted workforce training initiatives could be designed to focused on key competency areas. Further analysis could be done to identify clusters of mutually reinforcing or complementary skills, leading to more efficient training programs that address multiple skill deficiencies under one umbrella. For instance, technical equipment abilities, process monitoring, and inspection skills are likely to reinforce one another within the context of fabrication. Therefore, retraining programs designed to improve worker aptitude in any one of these skills will likely lead to positive spillover effects to other skill dimensions. Strategic and localized diagnosis of the pertinent limitations in skill-similar occupations' could prove an effective means of converting latent talent into viable labor in the semiconductor industry.

6 Discussion & Conclusion

The analytical framework and results we present are intended to provide an empirical foundation from which comprehensive analyses may be oriented, while delivering preliminary insights into the nature and scope of workforce supply challenges attendant to manufacturing capacity investments under CHIPS and Science. Our approach to estimating potential labor availability, which relies on the computation of skill similarity and skill readiness [11], occupational mobility, and granular spatial measures of employment and wage characteristics, is demonstrated for the case of the U.S. semiconductor industry amidst an influx of investment from federal industrial policy measures. We apply this framework to examine the impacts of increased investment on the stocks and flows of labor in a specific occupation, Semiconductor Processing Technicians (SMPs), based on their role in the semiconductor manufacturing industry, which received substantial funding from the CHIPS and Science Act. Regional characteristics in terms of existing employment and employment in skill-similar occupations as well as the variations in wage competitive are identified to be critical.

The results of our framework offer the possibility for policy-makers and private interest groups to structure their decisions, whether they pertain to funding decisions, supply chain optimization, or

[11] Note that while past similarity measures in this space, such as cosine similarity alone, have produced symmetric measures of distance between occupational pairs, our methodology is asymmetric because it incorporates a pairwise indexing over the inequality of skill level: occupation A may be more qualified to move into B, than B into A, and this distinction is vital for sourcing potential occupational transitions.

training and education program construction, in a manner that is likely to result in a more efficient alignment of resources and needs, leading to more effective outcomes.

There is significant variation in the wage distributions for occupations that are skill-similar to SMPs. This signals potential issues of efficacy for targeted recruitment programs, when attempting to address labor demand shocks. Incentivizing workers from other sufficiently skill-similar occupations to transition into roles within the Semiconductor industry may require significant wage premiums. Regional differences in SMP wage distributions, such as the comparison of Phoenix metro and Sherman-Denison wages, further complicates unified national recruitment strategies. Recruitment and training programs equipped with nuanced, localized understanding of existing labor force composition and wage expectations are better positioned to successfully align the supply and demand for critical manufacturing occupations equitably.

There is much work that remains to be done in this space, with the level of analytical granularity being a limiting factor of the current framework. At the forefront, we identify and acknowledge the limitations of the data used. Namely, that our analytical framework relies on publicly available data, which presents various limitations. First, the majority of the data used is aggregated at the annual level, which hinders our capabilities to offer insights to the labor market movements in response to regional and national economic conditions and shocks. Annual data does not include the short-term responses to shocks that may provide insights to the underlying factors driving occupational transitions, a characteristic that is necessary for effective estimations of potential labor flow responses.

Second, the crux of our approach is based on the skill taxonomy and occupational domain constructed by O*NET. While O*NET's skill profiles allow for comparisons across occupations via a standardized taxonomy, there are substantial limitations that we face. The primary limitations of the data we identify are that the profiles are essentially time invariant[12] and that the skills in the taxonomy are constructed to be broadly applicable across a wide variety of occupations and industries.

Third, the privacy requirements involved with publicly available data limits our ability to consider more granular geographic administrative boundaries. This limitation was critical in our approach to computing occupational mobility data, as occupational transitions at the state or MSA level is likely inaccurate within the CPS survey data environment. The privacy requirements are most present in our computation of the mobility data, as the OCC codes corresponding to the SOC codes are constructed in such a way that SOC codes are grouped at various SOC code taxonomy levels to ensure anonymity of survey respondents. This reduced our analytical capabilities as it reduced our pool of existing detailed SOC occupations from 715 occupations to 377 with mobility rates being spatially invariant. These privacy restrictions also hinder our ability to incorporate occupation-industry considerations, as regional employment data at the MSA-level for occupation-industry employment is not publicly available.

Finally, the spatial aggregation of the data is limiting in two distinct ways. The first pertains to the level of aggregation. According to the U.S. Census, MSAs and NECTAs are determined based on meeting the criteria of having "at least one urban area of 50,000 or more inhabitants." By construction, they do not capture administrative boundary effects that arise from local policies, such as county- or city-level minimum wages (Dube and Lindner, 2021). The second pertains to the lack of data on inter-MSA occupational transitions. Our data does not provide insights to labor movements across MSAs and as such, we are unable to incorporate the flows in and out of MSAs in the estimation of labor stocks and flows.

While these limitations are substantial, they may be addressed with the use of micro-level data

[12] Comparisons across releases may be possible, but as the occupations are not all updated with each release, the reliable comparison across time is likely to be problematic.

capturing trends across shorter time horizons for more granularly defined regions. There are sources available for the estimation of mobility flows and industry employment, such as Lightcast data, but this is beyond the consideration of this paper.

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A Appendix: Supplemental Materials

Table A.1: O*NET Work Activities

Domain	Type	Skills
Information Input	Looking for and Receiving Job-Related Information	• Getting Information • Monitoring Processes, Materials, or Surroundings
	Identifying and Evaluating Job-Relevant Information	• Identifying Objects, Actions, and Events • Inspecting Equipment, Structures, or Materials • Estimating the Quantifiable Characteristics of Products, Events, or Information
Mental Processes	Information and Data Processing	• Judging the Qualities of Objects, Services, or People • Processing Information • Evaluating Information to Determine Compliance with Standards • Analyzing Data or Information
	Reasoning and Decision Making	• Making Decisions and Solving Problems • Thinking Creatively • Updating and Using Relevant Knowledge • Developing Objectives and Strategies • Scheduling Work and Activities • Organizing, Planning, and Prioritizing Work
Work Output	Performing Physical and Manual Work Activities	• Performing General Physical Activities • Handling and Moving Objects • Controlling Machines and Processes • Operating Vehicles, Mechanized Devices, or Equipment
	Performing Complex and Technical Activities	• Working with Computers • Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment • Repairing and Maintaining Mechanical Equipment • Repairing and Maintaining Electronic Equipment • Documenting/Recording Information
Interacting With Others	Communicating and Interacting	• Interpreting the Meaning of Information for Others • Communicating with Supervisors, Peers, or Subordinates • Communicating with People Outside the Organization • Establishing and Maintaining Interpersonal Relationships • Assisting and Caring for Others • Selling or Influencing Others • Resolving Conflicts and Negotiating with Others • Performing for or Working Directly with the Public
	Coordinating, Developing, Managing, and Advising	• Coordinating the Work and Activities of Others • Developing and Building Teams • Training and Teaching Others • Guiding, Directing, and Motivating Subordinates • Coaching and Developing Others • Providing Consultation and Advice to Others
	Administering	• Performing Administrative Activities • Staffing Organizational Units • Monitoring and Controlling Resources

Table A.2: O*NET Abilities

Domain	Type	Skills
Cognitive Abilities	Attentiveness	• Selective Attention • Time Sharing
	Idea Generation and Reasoning Abilities	• Category Flexibility • Deductive Reasoning • Fluency of Ideas • Inductive Reasoning • Information Ordering • Originality • Problem Sensitivity
	Memory	• Memorization
	Perceptual Abilities	• Flexibility of Closure • Perceptual Speed • Speed of Closure
	Quantitative Abilities	• Mathematical Reasoning • Number Facility
	Spatial Abilities	• Spatial Orientation • Visualization
	Verbal Abilities	• Oral Comprehension • Oral Expression • Written Comprehension • Written Expression
Physical Abilities	Endurance	• Stamina
	Flexibility, Balance, and Coordination	• Dynamic Flexibility • Extent Flexibility • Gross Body Coordination • Gross Body Equilibrium
	Physical Strength Abilities	• Dynamic Strength • Explosive Strength • Static Strength • Trunk Strength
Psychomotor Abilities	Control Movement Abilities	• Control Precision • Multilimb Coordination • Rate Control • Response Orientation
	Fine Manipulative Abilities	• Arm-Hand Steadiness • Finger Dexterity • Manual Dexterity
	Reaction Time and Speed Abilities	• Reaction Time • Speed of Limb Movement • Wrist-Finger Speed
Sensory Abilities	Auditory and Speech Abilities	• Auditory Attention • Hearing Sensitivity • Sound Localization • Speech Clarity • Speech Recognition
	Visual Abilities	• Depth Perception • Far Vision • Glare Sensitivity • Near Vision • Night Vision • Peripheral Vision • Visual Color Discrimination

Table A.3: O*NET Skills

Domain	Type	Skills
Basic Skills	Content	• Reading Comprehension • Active Listening • Writing • Speaking • Mathematics • Science
	Process	• Critical Thinking • Active Learning • Learning Strategies • Monitoring
Cross-Functional Skills	Social Skills	• Social Perceptiveness • Coordination • Persuasion • Negotiation • Instructing • Service Orientation
	Complex Problem Solving Skills	• Complex Problem Solving
	Technical Skills	• Operations Analysis • Technology Design • Equipment Selection • Installation • Programming • Operations Monitoring • Operation and Control • Equipment Maintenance • Troubleshooting • Repairing • Quality Control Analysis
	Systems Skills	• Judgement and Decision Making • Systems Analysis • Systems Evaluation
	Resource Management Skills	• Time Management • Management of Financial Resources • Management of Material Resources • Management of Personnel Resources

Table A.4: O*NET Knowledge

Domain	Skill
Arts and Humanities	• English Language • Fine Arts • Foreign Language • History and Archeology • Philosophy and Theology
Business and Management	• Administration and Management • Administrative • Customer and Personal Service • Economics and Accounting • Personnel and Human Resources • Sales and Marketing
Communications	• Communications and Media • Telecommunications
• Education and Training	
Engineering and Technology	• Building and Construction • Computers and Electronics • Design • Engineering and Technology • Mechanical
Health Services	• Medicine and Dentistry • Therapy and Counseling
Law and Public Safety	• Law and Government • Public Safety and Security
Manufacturing and Production	• Food Production • Production and Processing
Mathematics and Science	• Biology • Chemistry • Geography • Mathematics • Physics • Psychology • Sociology and Anthropology
• Transportation	