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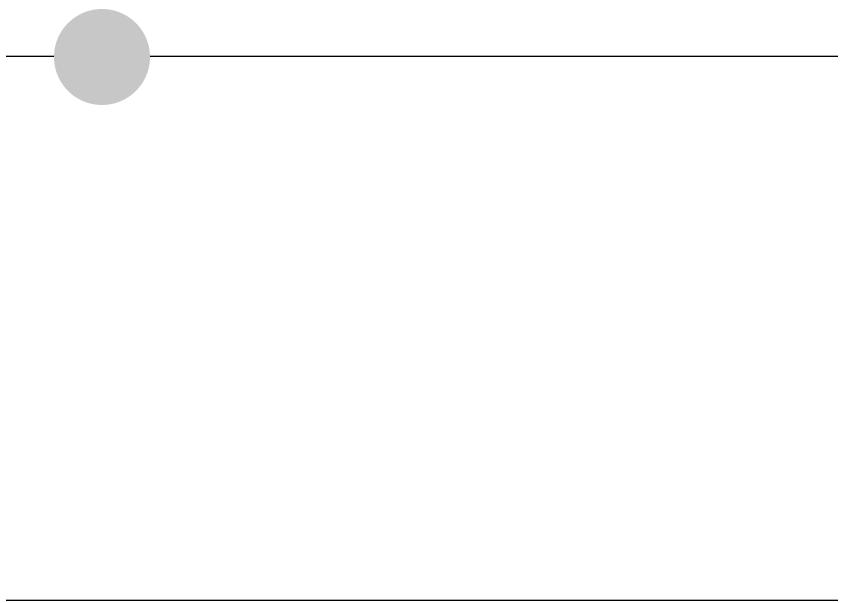
The Economics of Artificial Intelligence: An Agenda

Edited by

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5. Finding Needles in Haystacks: Artifi



public companies in the world by market capitalization. Table 19.2 lists the

a long history of Chinese export successes in other fields. Indeed, Sutton and Trefler (2016) describe both theoretically and empirically how developing

United States, Europe, and China. What is the current state of these domestic data regulations, how do they affect trade patterns, do they serve a public interest, are they being used as disguised protection to generate comparative advantage, and should they be covered by international trade agreements (as some would have been in the TPP e-commerce chapter)?

The following sections help answer these questions and move us toward better policies for promoting AI and preventing both corporate welfare and welfare-reducing disguised protection.

19.2 The Technological Backdrop: Scale, Scope, Firm Size, and Knowledge Diffusion

The Oxford English Dictionary defines AI as “the theory and development of computer systems ab

Top academic researchers have been hired to join Google (Hinton), Apple (Salakhutdinov), Facebook (LeCunn), and Uber (Urtasun). So far, there has been a meaningful difference between employing the elite researchers and others in terms of the capabilities of the AI being developed.

19.3.3 Economies of Scope

Perhaps more than economies of scale, the fixed cost of building an AI capacity generates economies of scope. It is only worth having an AI team within a company if there are a variety of applications for them to work

Shanghai, and to some extent Toronto and Montreal can all claim to be hubs of AI innovation. This suggests that AI involves a lot of tacit knowledge that is not easily codified and transferred to others.

In fact, the traditional discussion of knowledge externalities takes on a more nuanced hue in the context of AI. Can these researchers communicate long distance? Do they have to be together? How important are agglomeration forces in AI? As of 2017, AI expertise remains surprisingly rooted in the locations of the universities that invented the technologies. Google's DeepMind is in London because that is where the lead researcher lived. Then the first expansion of DeepMind outside the United Kingdom was to Edinburgh.

trade is weak. We then add on additional elements and examine which of these is important for policy success. The first conclusion is that scale and

forced McDonnell Douglas to exit. These EU subsidies were enormous, but

to scale, a government policy such as tariffs or production subsidies that increases domestic output will increase national welfare because the policy raises average productivity at home and also drive exports to sign country depend(s n, an

predictions from AI will be lower if the scale of data is limited to within a country. In other words, localization is a way to restrict the possible scale of any country in AI, but at the cost of lower quality overall.

Put differently, data localization is a privacy policy that could favor domestic firms. Unlike the consumer protection privacy policies highlighted above, it can favor domestic over foreign firms because the foreign-firm

could reduce the ability of foreign firms to maintain trade secrets. Furthermore, cyber espionage of such trade secrets may be widespread, but that is beyond the scope of this chapter.

19.6 Conclusion

How will artificial intelligence affect the pattern of trade? How does it make us think differently about trade policy? In this article we have tried to highlight some key points.

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