Automation, Career Values, and Political Preferences

Discussion

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I was delighted to have the opportunity to act as a discussant for this paper at the NBER Economics of Artificial Intelligence Conference, held in Toronto in September of 2024.

Based on rich individual-level data, the authors estimate the career value of occupations, combining information on the likelihood of transitions across occupations with the earning potential of these occupations. The paper documents a downward trend in the growth of career values in the US between 2000 and 2016. This is mostly driven by reduced upward occupational mobility. At the commuting zone level, higher exposure to robot adoption lowers average career values. The effect is more pronounced for low-skilled individuals. Lower career values, in turn, are related to lower investment in schooling and housing, and to higher electoral support for candidate Trump in the 2016 presidential elections.

I find the focus on career values very interesting, as they provide an important summary indicator of labor market dynamics. Overall, I think the analysis is rich and carefully executed. I also appreciate that the study spans beyond labor market dynamics, although this comes perhaps at the risk of some loss in focus. In my discussion, I have made some comments about the instrumental variables strategies adopted in the paper, and about the way in which some of the results are interpreted. I hope these can be useful as the authors finalize their work for publication. I summarize my points in what follows.

In the spirit of Acemoglu and Restrepo (2020), the authors instrument robot adoption in the US using robot adoption in European countries. The intuition behind this approach is that of exploiting technological trajectories that are: (1) relevant for automation; (2) common across countries; and (3) exogenous to local conditions across US labor markets. I am sympathetic with this approach, which I have employed in my own work joint with Massimo Anelli and Piero Stanig (Anelli *et al.*, 2019 and Anelli *et al.*, 2021). However, there may be a problem with the exclusion restriction, due to the presence of demand and supply shocks that are correlated across countries. This limitation is particularly evident if one thinks of the automotive industry, where the largest share of robots is adopted. Here we have that the same companies are often producing both in the US and in Europe (e.g., Ford and FCA), leading to decisions about robot adoption in these two geographical contexts that are ultimately under the control of the same management. The role of correlated shocks seems to be actually relevant for the results. For instance, if one looks at Table 3, the power of the instrument is much lower in the period after the financial crisis of 2008, which is when the business cycles of the US and Europe diverge.

Having faced this problem in my own work, I have suggested a possible alternative instrumental variables approach, as introduced in an updated version of Anelli *et al.* (2019), and later in Anelli *et al.* (2021). In particular, in our cross-country European analysis we define:

$$\text{IV Regional Exposure}_{crt} = \sum_j \frac{L_{crj}^{\text{pre-sample}}}{L_{cr}^{\text{pre-sample}}} * \text{Rep}_\text{j} * \Delta\text{Index}_{\text{t}-1,\text{t}-\text{n}} \tag{1}$$

where c indexes countries, r regions, and t years. $\frac{L_{crj}^{\text{pre-sample}}}{L_{cr}^{\text{pre-sample}}}$ is the pre-sample share of each industry out of the total employment of each region. Rep_j is an industry-level replaceability index—i.e., the share of hours worked within industry j in occupations replaceable by robots—as computed by Graetz and Michaels (2018) based on US Census data of 1980. $\Delta\ Index_{t-1,t-n}$ is the change in either: (1) average unit price of industrial robots sold in the US (IFR); (2) producer index of computer prices (Fred); (3-4) two indexes of advances in computing, specifically single-thread performance and number of transistors per microprocessor. The idea behind this approach is to capture more directly global technological shifts in robots and computing that matter for automation, with heterogeneity across industries driven by their ex-ante replaceability score. While the first two indexes may be problematic in this context, given the focus on the US, the other indexes may prove useful for an alternative IV approach.

In Table 4, the power of the instrument seems to vary substantially across columns. In particular, the result in column 1 seems rather weak. Similar considerations apply elsewhere in the paper. I was wondering if this is an implication of the IV Lasso approach. As a baseline, I think it would be better to exploit the same identifying variation across different regressions, especially when the comparison of magnitudes across specifications is so important.

When focusing on the effect of career value changes at the commuting zone level, the authors introduce a new instrument. Specifically, they instrument the average career value of a commuting zone using the career values of sufficiently similar but distant communities. These are identified as commuting zones in states outside a 100-mile radius around the commuting zone of interest. The motivation behind this approach is not spelled out, and I am wondering where the power of this instrument come from. If it comes from macro dynamics that are common across different areas of the US, then again there could be a problem with the exclusion restriction. As an alternative, one could select for the instrument commuting zones that are similar according to pre-sample characteristics, for instance in terms of the composition of employment across industries.

I have a more general comment about the way in which results are interpreted in the analysis of the effects of career values, for instance in Table 12. The authors interpret the effect of career value changes as an effect of long-run expectations held by individuals. However, career values also embody current income, which is likely to be relevant for housing, schooling, and voting decisions. This could be more openly acknowledged. If the authors want to disentangle the role of expectations from the role of current conditions, then they should find a way to separate the two pieces of information in the analysis.

As concluding remarks, I would suggest to enrich and clarify the discussion of mechanisms, especially concerning changes in consumption. I am wondering that consumer responses may be seen more as an outcome rather than a mechanism. I would also suggest to provide more information on how occupational mobility is evaluated. In particular, upward vs. downward mobility based on wages is clear, while other measures are less obvious. For instance, a transition from production to architecture/engineering seems to be constrained by education/qualifications. This is something that could be discussed more. Finally, the analysis spans the period of the Great Financial Crisis of 2007-2008, but the possible implications for the results are not discussed. I would recommend the authors to engage with this.

Overall, I think there is a lot of value in this work. I hope my comments can be useful for improving it further, and I hope to see it published in the near future.

References

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