The Adaptive Investment Effect: Evidence from Chinese Provinces*

Kamiar Mohaddes[a] and Rhys J. Williams[b†]
[a] Judge Business School and King's College, University of Cambridge, UK
[b] London Economics, UK

24 April, 2020

Abstract

This paper investigates the so-called "adaptive investment effect", a redirection of investment in productive capital towards adaptive capital with a view to mitigating the negative effects of climate change. We estimate the costs associated with the adaptive investment effect using data on Chinese provinces and find that the impact of investment on economic growth is reduced by between 27% and 37% in provinces investing more in adaptive capital. This implies that the social cost of carbon is higher than existing studies suggest, making it more urgent for policymakers to take action against climate change.

JEL classifications: C33, O40, O53, Q51, Q54.
Keywords: Climate change, adaptation, investment, China.

1 Introduction

Adaptation is vital to mitigate some of the negative long-run growth effects of climate change (Kahn et al. 2019). It is argued that in the absence of adaptation, labour productivity impacts would be three times greater than in a situation in which all agents invest an optimal amount in adaptive technologies (Park 2017). Furthermore, if no further adaptation were to occur in China, then by the middle of the century, climate change would reduce Chinese manufacturing output by 12% year-on-year, leading to a reduction in welfare equivalent to 3.8% of Chinese GDP annually (Zhang et al. 2018). This highlights the potential costs of climate change and the necessity for adaptation. However, adaptation requires the diversion of funds from productive capital investment and research and development activities towards adaptive technologies. Therefore, we expect adaptation itself to have a negative effect on productivity in the long-run as adaptive capital is assumed to be inherently unproductive. We term this diversion of funds the "adaptive investment effect" (AIE).

Trying to understand whether this effect has had a meaningful impact on an economy and the magnitude of any such effect is an important research question for three reasons. Firstly, the results are important to incorporate in Integrated Assessment Models (IAMS)[1] in order to estimate the cost of climate change and advise policymakers on the benefits of abatement policies. Clearly, failing to include costs, such as the AIE studied in this paper, within these IAMs leads to an underestimation of the costs of carbon emissions and climate change (Sterner et al. 2014). Secondly, growth rates compound, so the effect of even a small change in output growth from the adaptive investment effect could be large. Thirdly, there is likely to be a large diversion of funds from investment capital toward developing adaptive infrastructure which will impose a cost to society from

*This work was conducted whilst Rhys J. Williams was at Girton College, University of Cambridge. We are grateful to Tiago Cavalcanti, Zeina Hasna, Michael Kitson, Michael Pollitt, David Reiner and Deborah Williams for helpful comments and suggestions.

†Corresponding author: rhysjwilliams@cantab.net

[1]See for instance Nordhaus (1991) and Tol (2018).

a loss of productivity-enhancing investment. Current cost estimates of the necessary adaptive infrastructure stock range from $25-100 billion a year over the period 2015-30 (Fankhauser 2009).

Whilst Pindyck (2013) suggests that resources used to adapt to a warming climate will reduce those which can alternatively be used in productive capital investment or R&D, thereby lowering growth, the literature on adaptation focuses on the direct costs and challenges of adaptive investment without studying the costs of diverting funds away from productive capital (e.g. Somanathan et al. 2014, Graff Zivin et al. 2018). To the best of our knowledge this paper is the first attempt to empirically examine the adaptive investment effect. More specifically, we investigate the implications of the adaptive investment effect using provincial data from China over the period 1993 to 2012. As the world's largest economy (in PPP GDP terms) and greenhouse gas emitter, contributing 23% of world emissions (Cohen et al. 2018), China is likely to be greatly affected by the AIE and it is therefore important to examine its magnitude based on within country data. We show that the adaptive investment effect reduces the long-run impact of investment on output growth by between 27% and 37%, across Chinese provinces, a substantial amount, although those provinces which have adapted are also able to offset some of the negative effects of climate change.

2 Empirical Results

To investigate the implications of the adaptive investment effect for China we compare the effects of investment on economic growth in regions that have suffered more from climate change and invested heavily in adaptive capital with those regions which have not invested in adaptive capital. Furthermore, we test whether adaptive investment is actually insulating regions against the negative economic effects of climate change (Kahn et al. 2019). To this end we estimate the following panel autoregressive distributed lag model (ARDL):

$$\Delta y_{it} = \alpha_i + \sum_{l=1}^{p} \phi_{il} \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}_{il} \Delta \mathbf{x}_{i,t-l} + u_{it} \tag{1}$$

Where y_{it} is the log of gross regional product per capita for province i in year t, $\mathbf{x}_{i,t} = \{I_{i,t}, T_{i,t}\}$ where $T_{i,t}$ represents the average annual temperature and $I_{i,t}$ is the log of investment per capita. We obtain gross regional product and investment data over the period 1993-2012 for 29 provinces from the National Bureau of Statistics of the People's Republic of China (NBS). Moreover, using data from the World Bank's Climate Division, we construct provincial temperature data.[2]

We estimate equation (1) and obtain the long-run effects, $\boldsymbol{\theta_i}$, from the OLS estimates of the short-run coefficients, using:

$$\boldsymbol{\theta}_i = \frac{\sum_{l=0}^{p} \boldsymbol{\beta}_{il}}{1 - \sum_{l=1}^{p} \phi_{il}} \tag{2}$$

To obtain the pooled mean group (PMG) estimates, the individual long-run coefficients

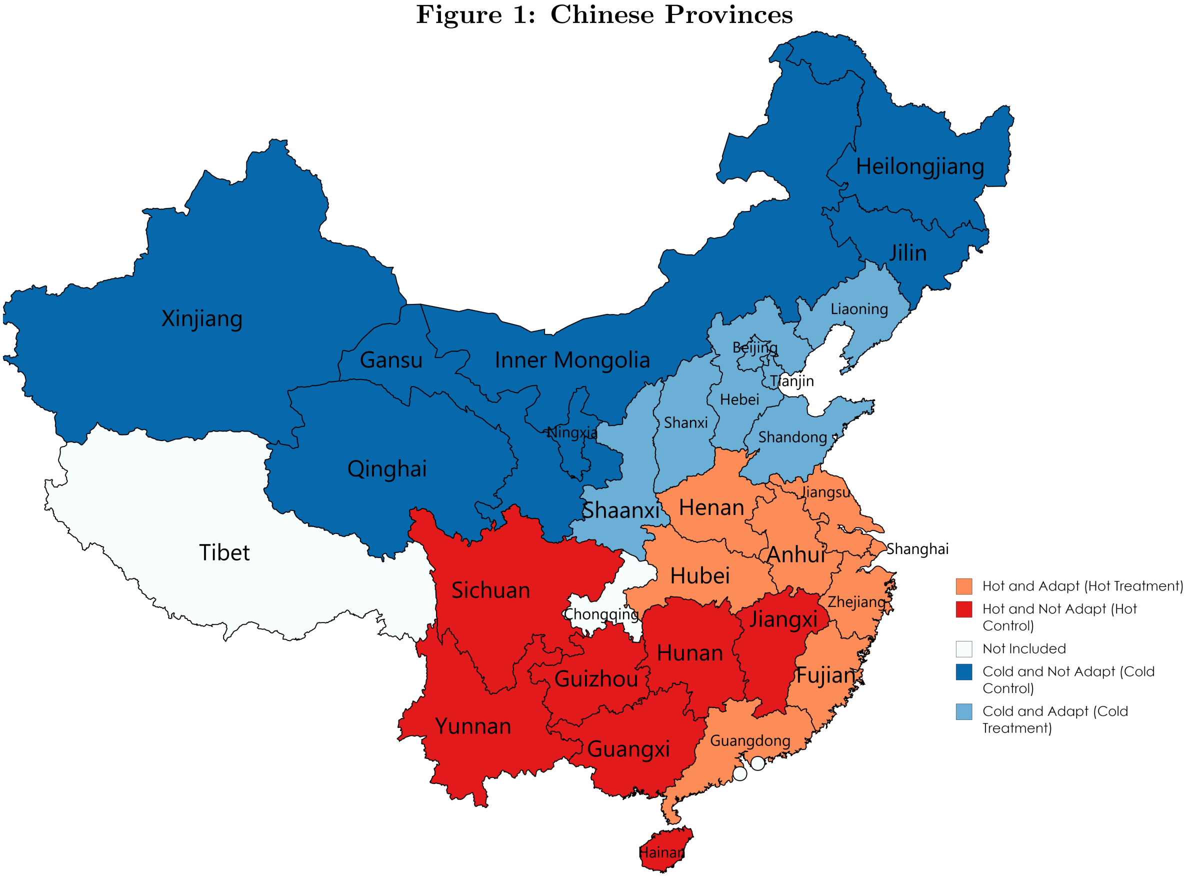
[2]We have base station temperature data from the 5 largest cities (by population) in each province.

are restricted to be the same across provinces, namely

$$\boldsymbol{\theta}_i = \boldsymbol{\theta} \qquad i = 1, ..., N \tag{3}$$

Pesaran & Smith (1995), Pesaran (1997) and Pesaran & Shin (1995) show that the the traditional ARDL approach can be used for long-run analysis; is valid regardless of whether the underlying variables are $I(0)$ or $I(1)$; and is robust to omitted variable bias and bi-directional feedback effects between economic growth and its determinants. These features of the panel ARDL approach are clearly appealing in our empirical application. However, sufficiently long lags are necessary for the consistency of the panel ARDL approach (Chudik et al. 2016). Since the impact of climate change on output growth could be long lasting, the lag order should be long enough, and as such we set $p = 3$ for all variables and provinces. Note also that our primary focus here is on the long-run estimates rather than the specific dynamics that might be relevant for a particular province.

Figure 1: Chinese Provinces



Notes: Based on author's calculations. Tibet and Chongqing are excluded from the analysis due to data availability.

We split our sample into hot and cold provinces, and within these sub-samples, compare provinces with a high level of adaptation against provinces with a low level. See Figure 1 for a breakdown of provinces included in each sub-sample. This allows us to disentangle the AIE from possible climate change effects, which we would expect to lead to lower marginal productivity of investment (MPI) compared to regions less affected by climate change.

As a proxy variable for adaptive investment we use the number of air-conditioners.[3] This

[3] Air-conditioner usage is far from the only source of adaptive technology but readily available data makes it an easy

is considered a typical example of an adaptive measure to climate change (e.g. Kahn & Zhao 2018). Using U.S. data on state-level air-conditioning rates, Barreca et al. (2015) find that the mortality impacts of heat stress have been reduced by around 75% and that most of this reduction is the result of adopting air-conditioning. States which experienced the highest risks of heat-related mortality adapted by purchasing air-conditioning, whereas lower exposure states did not. Therefore, we would expect to see a similar effect in China, with the provinces most affected by climate change investing heavily in air-conditioning as a form of adaptive capital. We obtain information on the number of air-conditioners per household from the NBS annual rural and urban survey run between 1993 and 2012.[4]

Table 1: Estimates of the Long-run Effects of Investment and Temperature on Output Growth for the Hot Province Sub-sample, 1993-2012

(a) Long-run Effects of Investment on Output Growth

	Fixed Effects			Pooled Mean Growth		
	1 lag	2 lags	3 lags	1 lag	2 lags	3 lags
Treatment	0.391***	0.439***	0.408***	0.431***	0.455***	0.413***
	(0.0351)	(0.0379)	(0.0348)	(0.0258)	(0.0211)	(0.0147)
Control	0.425***	0.500***	0.454***	0.439***	0.572***	0.588***
	(0.0553)	(0.0595)	(0.0691)	(0.0434)	(0.0407)	(0.0272)

(b) Long-run Effects of Temperature on Output Growth

	Fixed Effects			Pooled Mean Growth		
	1 lag	2 lags	3 lags	1 lag	2 lags	3 lags
Treatment	-0.052	-0.088*	-0.029	-0.052*	-0.115**	0.024
	(0.0323)	(0.0521)	(0.0502)	(0.0314)	(0.0505)	(0.0300)
Control	-0.088	-0.308***	-0.300***	-0.112**	-0.428***	-0.222***
	(0.0573)	(0.1024)	(0.1154)	(0.0544)	(0.1042)	(0.0778)

Notes: Treatment group is hot and adapt, control group is hot and not adapt. Symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

We report the estimates of equation (1) for the hot province sub-sample in Table 1 based on both the FE and PMG estimators but will focus on the PMG results given that it allows us to capture the inherent heterogeneity across Chinese provinces. As can be seen, the hot treatment sub-sample has a lower MPI than the control sub-sample for each lag. In other words, amongst hot provinces, those which adapt have a lower MPI than those which do not adapt. Furthermore, amongst hot provinces, those which adapt successfully insulate themselves against the effects of temperature, as seen by the lower (and in some cases insignificant) coefficients of temperature in the treatment sub-sample relative to the

proxy for the wide-ranging variety of adaptive technologies that exist in reality.

[4]Data for 2002-2012 is taken from the NBS website, which is available for both rural and urban households, whilst data for 1993-2002 is gathered from the physical copies of the Chinese Statistical Yearbooks and is only available at the provincial level for urban households. This data series was discontinued in 2012. A drawback of this variable is that it is only available for residential and not commercial units. However, businesses in China are required to implement protective measures such as providing air-conditioning during extremely hot days (Zhang et al. 2018), so we would expect residential and firm air-conditioning investment to be highly correlated.

Table 2: Estimates of Long-run Effects of Investment and Temperature on Output Growth, 1993-2012

Long-run Effects of Investment on Output Growth				Long-run Effects of Temperature on Output Growth			
Fixed Effects		Pooled Mean Growth		Fixed Effects		Pooled Mean Growth	
Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
(a) 15 Hottest Provinces							
0.408***	0.454***	0.413***	0.588***	-0.0292	-0.300***	0.0242	-0.222***
(0.0348)	(0.0691)	(0.0147)	(0.0272)	(0.0502)	(0.115)	(0.0300)	(0.0778)
(b) 14 Coldest Provinces							
0.379***	0.426***	0.378***	0.520***	-0.0749	-0.1070	-0.00745	-0.103***
(0.0551)	(0.0832)	(0.0339)	(0.0490)	(0.0535)	(0.0652)	(0.0348)	(0.0378)
(c) 15 Highest-trend Provinces							
0.385***	0.432***	0.324***	0.512***	-0.0554	-0.0786	-0.0209	-0.0616**
(0.0452)	(0.0557)	(0.0352)	(0.0413)	(0.0542)	(0.0488)	(0.0350)	(0.0314)
(d) 14 Lowest-trend Provinces							
0.469***	0.379***	0.427***	0.632***	-0.0413	-0.441***	0.0431	-0.702***
(0.0380)	(0.103)	(0.0147)	(0.0561)	(0.0652)	(0.126)	(0.0335)	(0.0335)

Notes: Treatment group is high air-conditioner rate (adapting), control group is low air-conditioner rate (non-adapting). Symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. p=3 for all variables and provinces.

control.

To ensure our results are not just an artefact amongst the hot provinces, we re-estimate equation (1) for the cold sub-sample, reporting the results in panel (b) of Table 2. Within cold provinces, those which have invested in adaptive capital have a lower MPI compared to provinces which have not invested in adaptive capital. We also observe that this adaptive investment successfully insulates against the effects of climate change as the coefficient of temperature is insignificant in the treatment group, but negative and significant in the control group. As additional robustness checks, we re-estimate equation (1) splitting the sub-samples according to temperature trends rather than absolute temperature, which perhaps better captures the effects of climate change. The results are reported in panels (c) and (d) of Table 2 and confirm the robustness of the adaptive investment effect.

Across all sub-samples, the adaptive investment effect decreases the MPI by between 0.14 and 0.21 percentage points based on the PMG specifications. This translates to a reduction in MPI of 27% to 37%. There might be a concern that increasing demand for air-conditioning in recent years has been driven by rising incomes and population growth, not due to a sharp increase in the effects of climate change (IEA 2018). We test for this, by only considering a sample of the 14 richest provinces (of which 7 have adapted) and re-estimate equation (1). Our results are consistent with those in Tables 1 and 2 suggesting that our findings are driven by the AIE and not an income effect. These results are not reported here but are available upon request.[5]

[5] We also re-estimate the specifications in Table 2 with alternative sub-samples to ensure that the results are not driven by one or two provinces. Moreover, we use the average temperature based on a longer time period (1960 to 2012) to select our sub-samples. In both cases our results are found to be consistent with those in Tables 1 and 2.

3 Concluding Remarks

This paper is a first attempt at examining the so-called "adaptive investment effect", a redirection of investment in productive capital towards adaptive capital so as to mitigate the negative effects of climate change. Using province level data from China, we provide evidence for the adaptive investment effect. More specifically, we find that for those provinces which have invested in adaptive capital, the long-run effects of investment on output growth is reduced by between 27% and 37%, although these provinces are able to offset some of the negative effects of climate change. Therefore, the adaptive investment effect makes the benefits from mitigation policies greater than the existing studies suggest, and implies that we need urgent action to fight climate change.

References

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2015. "Will Adaptation to Climate Change be Slow and Costly? Evidence from High Temperatures and Mortality, 1900-2004." *Becker Friedman Institute for Research In Economics Working Papers, BFI-2015-02.*

Chudik, Alexander, Kamiar Mohaddes, M Pesaran, and Mehdi Raissi. 2016. "Long-Run Effects in Large Heterogeneous Panel Data Models with Cross-Sectionally Correlated Errors." In *Essays in Honor of Aman Ullah.* Vol. 36, 85–135. Emerald Publishing Ltd.

Cohen, Gail, Joao Tovar Jalles, Prakash Loungani, Ricardo Marto, and Gewei Wang. 2018. "Decoupling of Emissions and GDP: Evidence from Aggregate and Provincial Chinese Data." *IMF Working Paper, WP/18/85.*

Fankhauser, Samuel. 2009. "The Costs of Adaptation." London School of Economics and Political Science.

Graff Zivin, Joshua, Solomon M. Hsiang, and Matthew Neidell. 2018. "Temperature and Human Capital in the Short and Long Run." *Journal of the Association of Environmental and Resource Economists*, 5(1): 77–105.

IEA. 2018. "The Future of Cooling." *International Energy Agency*, 1–92.

Kahn, Matthew, and Daxuan Zhao. 2018. "The Impact of Climate Change Skepticism on Adaptation in a Market Economy." *Research in Economics*, 72(2): 251–262.

Kahn, Matthew, Kamiar Mohaddes, Ryan N. C. Ng, M Pesaran, Mehdi Raissi, and Jui-Chung Yang. 2019. "Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis." *National Bureau of Economic Research, Working Paper 26167.*

Nordhaus, William. 1991. "To Slow or Not to Slow: The Economics of the Greenhouse Effect." *Economic Journal*, 101(407): 920–37.

Park, Jisung. 2017. "Will We Adapt? Temperature Shocks, Labor and Adaptation to Climate Change." *Harvard Project on Climate Agreements Working Papers.*

Pesaran, M. 1997. "The Role of Economic Theory in Modelling the Long Run." *Economic Journal*, 107(440): 178–91.

Pesaran, M., and Ronald Smith. 1995. "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels." *Journal of Econometrics*, 68(1): 79–113.

Pesaran, M., and Yongcheol Shin. 1995. "An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis." Cambridge Working Papers in Economics 9514.

Pindyck, Robert. 2013. "Climate Change Policy: What Do the Models Tell Us?" *Journal of Economic Literature*, 51(3): 860–72.

Somanathan, E., Rohini Somanathan, Anant Sudarsan, and Meenu Tewari. 2014. "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing." eSocialSciences Working Papers.

Sterner, Thomas, Richard L. Revesz, Peter H. Howard, Kenneth Arrow, Lawrence H. Goulder, Robert E. Kopp, Michael A. Livermore, and Michael Oppenheimer. 2014. "Global Warming: Improve Economic Models of Climate Change." *Nature*, 508: 173–175.

Tol, Richard. 2018. "The Economic Impacts of Climate Change." *Review of Environmental Economics and Policy*, 12(1): 4–25.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang. 2018. "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants." *Journal of Environmental Economics and Management*, 88(C): 1–17.