Report #3: The Relationship Between Air Conditioning Adoption and Temperature

Author: Maximilian Auffhammer,
Associate Professor UC Berkeley ARE/IAS

Prepared for:

Stephanie Waldhoff and Elizabeth Kopits
U.S. Environmental Protection Agency
1200 Pennsylvania Ave., N.W.
Washington, DC 20460

October 12, 2011

1. Introduction

The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) reports that the best estimates of global mean temperature increases by the end of century range from 1.8 to 4° Celsius. Many sectors of the global economy will be directly affected by this warming in economically significant ways (e.g., agriculture and health). Intensities of and strategies for adaptation will vary by sector. This review examines one major currently available measure of adaptation: the adoption of air-conditioning units by households.

Individuals take exterior temperatures and relative humidity levels as a given, yet can, at a fairly low cost, control temperatures and relative humidity levels by investing in central or room air-conditioning units to increase their comfort levels. In a world without climate change, adoption of air conditioners can be thought of as a traditional adoption problem, where the decision to adopt depends on the capital cost, the cost of operation (e.g., the price of electricity and the efficiency of the unit), and income. Historical evidence shows that rising incomes and efficiencies, as well as the dropping prices of the units, have led to increased penetration rates. Data also show that hotter locations, conditional on income, have higher penetration rates. This suggests that over time regions that currently require little indoor cooling may experience higher saturation rates as climate change shifts temperature distributions upward. Conceptually, rising incomes and falling prices therefore drive penetration rates toward an increasing level of saturation over time. Saturation is therefore no longer exogenous but endogenous due to climate change. If penetration rates are outstripping the rates of efficiency improvements in air conditioners, the cooling season electricity consumption will increase and the load profile will become "peakier."

In this paper we are interested in understanding long-term trends in air conditioning adoption and how it varies between developed and developing countries as an indication of what might occur with regard to energy consumption. Some integrated assessment models [e.g., the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) model] attribute a large share of the damages due to rising global mean temperature to higher cooling expenses. The parameterization of the energy consumption modules of these models in many cases is rudimentary and relies on outdated studies of energy demand (in the case of FUND, Downing et al., 1996a, 1996b).

The goal of this report is twofold. Section 2 provides a selective survey of the empirical literature on the adoption of air conditioning and its determinants. The literature review breaks out our current understanding of the differences in the adoption function by geographic region. Section 3 briefly overviews existing datasets, which have been used to estimate energy demand for cooling, with particular attention paid to the relationship between temperature and the rate of adoption of air conditioning. Section 4 empirically examines the relationship among summer temperature, income, and the adoption of air conditioners in urban and rural China from 1995 to 2008. Section 5 compares the penetration rates from these relationships to observed penetration rates in the United States. We conclude that the current penetration of air conditioning in China is similar to the rates observed in the United States in 1993 – 8–12% of the personal income levels – suggesting that developing countries adopt at much lower levels of income, which is likely due to lower prices and higher efficiencies of current air-conditioning units.

2. Literature Review

This section provides a selective review of the literature dealing with the adoption of air conditioners in the United States and abroad. In summary, most empirical papers, largely due to data availability concerns, estimate models based on cross sections or repeated cross sections. As shown in Section 4, using panel data approaches to control for unit and time fixed effects can influence parameter estimates significantly. Data collection efforts enabling panel data approaches will add a meaningful dimension to this literature. Table 1 lists the papers examined in this literature review.

Table 1. Summary of studies discussed in the literature review

Paper	Data	Location	Price elasticity	Income elasticity
Biddle (2008)	Repeated and pooled cross sections	United States	[-0.12; -0.59] Room [-1.4; -0.26] Central	[0.13; 0.37] Room [0.78; 1.76] Central
Sailor and Pavlova (2003)	Cross section	United States	N/A	N/A
Rapson (2011)	Repeated cross section	United States	[-0.116; -0.127] Room [-0.241; -0.248] Central	N/A N/A
EIA (2011a)	Panel (based on micro survey)	United States	N/A	N/A
DGTE (2003)	Cross section	Europe	N/A	N/A
Aebischer et al. (2007)	Cross section	Europe	N/A	N/A
McNeil and Letschert (2005)	Cross section	Developing countries	N/A	N/A
McNeil and Letschert (2008)	Cross section	Developing countries	N/A	N/A

Table 1. Summary of studies discussed in the literature review (cont.)

Paper	Data	Location	Price elasticity	Income elasticity
Letschert and McNeil (2009)	Cross section	Developing countries	N/A	N/A
McNeil and Letschert (2010)	Cross section	Developing countries	N/A	N/A
Letschert et al. (2010)	Time series	China	N/A	N/A
Isaac and van Vuuren (2009)	Cross section	Global	N/A	N/A
Akpinar-Ferrand and Singh (2010)	Cross section and time series	India	NA	N/A
Downing et al. (1996a)	Cross section	Global	N/A	N/A
Downing et al. (1996b)	Cross section	Global	N/A	N/A
SEI (1993)	Cross section	Global	N/A	N/A

2.1 United States

Biddle (2008) studies the spread of air conditioning in the United States in the post-World War II economy. In the early 1950s, air conditioners were mainly found in public spaces (e.g., movie theatres and supermarkets). He notes that in 1955 the residential air conditioner penetration in the United States was below 2% nationally. A quarter of a century later that fraction had risen to 50%, with half of those households having installed central air-conditioning units. There was significant heterogeneity in the penetration, where half the residences in the Northeast were air conditioned and some urban areas in Texas and Florida had penetration rates in excess of 90%. Table 2 (Biddle, 2008, Table 1) shows the breakdown of air conditioning by Census Division over this 20-year period.

Table 2. Owner-occupied housing air conditioning

	1960	1970	1980
US totals	12.6%	35.8%	58.5%
By census division			
New England	4.9	17.8	34.3
Middle Atlantic	11.5	33.2	45.8
East North Central	8.7	29.6	50.1
West North Central	15.2	41.3	64.8
South Atlantic	13.2	45.2	76.1
East South Central	15.6	45.7	66.5
West South Central	27.2	60.6	81.7
Mountain	11.2	29.7	47.6
Pacific	8.3	21.1	33.8

Source: Biddle, 2008, Table 1.

Biddle (2008) points out that in the early 1950s the way in which homes were built changed fundamentally. Due to the increasing separation between builders and owners, mass-produced homes built by developers were less likely to be optimally built (e.g., taking into account prevailing winds, patterns of sunlight, and landscape features in order to create a more pleasant indoor environment, Biddle, 2008, p. 404) Further, the Federal Housing Authority announced in 1957 that the cost of air conditioning could be rolled into approved mortgage packages, which led to a jump in installations. Finally, Biddle provides an interesting back-of-the-envelope calculation suggesting that the extensive population shifts during this period can only account for a fraction of the changes in penetration over time. He shows that after adjusting for efficiency gains and inflation, the price of air conditioners dropped by 25% during the 1970s and another 20% during the 1980s.

Further, electricity prices dropped significantly during the 1950s and 1960s and then rose again during the 1970s. During this period incomes rose substantially, which suggests that the falling costs of installation and operation, combined with rising incomes, drove the adoption of air conditioners during this time. In order to determine the relative importance of these factors, Biddle (2008) matches the air-conditioning indicators with the corresponding socioeconomic characteristics from three Census cross sections for 1960, 1970, and 1980 to electricity rates in the Standard Metropolitan Statistical Area (SMSA), incomes, and detailed climate variables [e.g., cooling and heating degree days (HDDs), wind speed, relative humidity]. He uses a reduced form econometric model, which accounts for changes in incomes, prices, and weather to explain the heterogeneity in penetration.

Biddle (2008)shows that differences in climate across SMSAs explain 75–95% of the variation in penetration in the cross section relative to the models, which also control for prices and socioeconomic factors. He also shows that the home characteristics relevant to retrofitting played a significant role. Table 3 (Biddle, 2008, Table 5) lists the estimated income and price elasticities for the three Census years, which are broken down by age of residence and type of air-conditioning unit.

The income elasticities are positive in most specifications and years, even though they vary widely in size and significance across samples and estimation techniques. The price elasticities are generally negative and often significant, although they also vary significantly in magnitude. Biddle (2008) concludes that while rising incomes and dropping real prices of electricity drove the adoption of air conditioners in the United States during the 20-year study period, the changing housing stock impacted the costs of adopting air conditioning, which accelerated these trends. He shows weaker evidence that significant drops in the initial cost of installing air conditioners also promoted the adoption of these units. He is careful to point out that these results may be confounded by improved efficiency of the air-conditioning units and changes in the housing stock, which he cannot control for.

Table 3. Estimated income and price elasticities

	WLS[a]	Logistic[b]	Log–Log[c]
1960 Room			
Price elasticity	−.59*	−.24	−.06
Income elasticity	.13	1.07*	.82*
1960 Central			
Price elasticity	−1.40*	−.98*	−1.4*
Income elasticity	1.76*	1.01*	−.20
1970 Room			
Price elasticity	−.20+	−.14	.27
Income elasticity	.37	.72*	.97*
1970 Central, recently built residences			
Price elasticity	−.03	.05	.01
Income elasticity	.60+	1.15*	.29
1970 Central, older residences			
Price elasticity	−.57	−.59+	−.91*
Income elasticity	1.04	.67	−.32
1980 Room			
Price elasticity	−.12*	−.05	−.06
Income elasticity	.35*	.51*	.51*
1980 Central, recently built residences			
Price elasticity	−.21*	−.18*	.09
Income elasticity	.18+	.44*	.37+
1980 Central, older residences			
Price elasticity	−.70*	−.42*	−.45*
Income elasticity	1.37*	1.13*	.66*

[a] Elasticity estimates based on the WLS regressions reported in Tables 3 and 4.
[b] Elasticity estimates based on logistic regressions, with same independent and dependent variables as used in the WLS regressions.
[c] Elasticity estimates based on OLS regressions in which the dependent variable is the log of the relevant air conditioning share; the electricity rate, income, heating degree days, and cooling degree days are logged in the left hand side, and all other independent variables are the same as in the WLS regressions.
* Significant at 5%.
\+ Significant at 10%.

Source: Biddle, 2008.

Sailor and Pavlova (2003) use data on air conditioning penetration for 39 U.S. cities to parameterize a relationship between cooling degree days (CDDs) and market saturation. They take issue with existing estimates that electricity consumption rises by 2–4% for each degree Celsius in warming as these estimates only account for intensive margin adjustments (more frequent operation of existing air-conditioning equipment). A hotter future will result in extensive margin adjustments, namely higher saturation levels. Figure 1 shows their penetration data from the American housing survey for 39 cities for the years 1994–1996 for both central and window units.

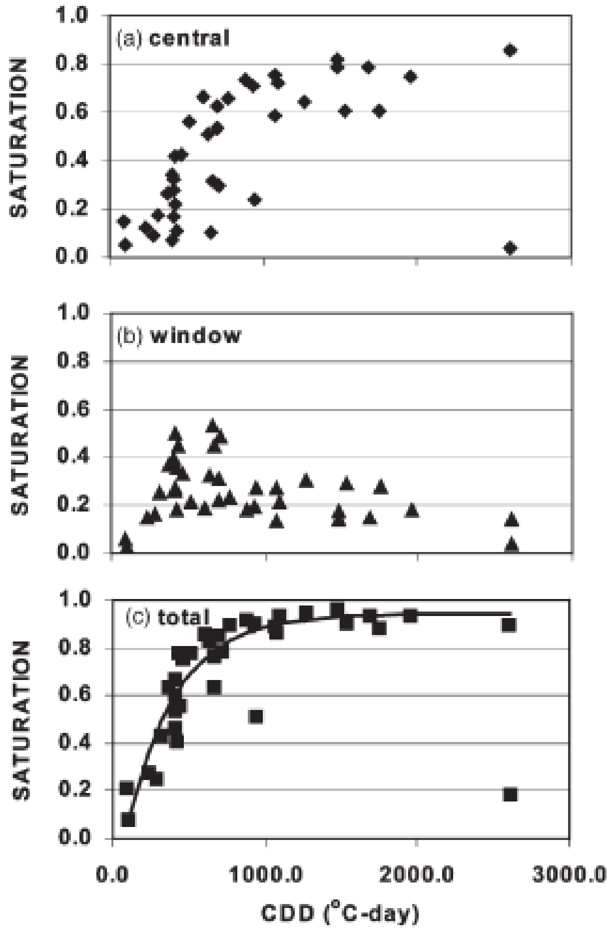

Figure 1. Penetration of air conditioners by type for 39 U.S. cities.

Source: Sailor and Pavlova, 2003.

Figure 1 also shows that a significant number of cities have air conditioning penetration below 80%, which suggests that there is room for the two temperature-driven margins of adjustment under climate change: increased adoption of air conditioners and increased usage. Ignoring the adoption decision would lead to an underestimation of future electricity consumption. Sailor and Pavlova (2003) estimate a relationship between saturation and CDDs for the combined saturation plot (Figure 1, panel c). They estimate an equation between what they call “saturation” (which is the recent penetration from the 1994 to 1996 American Housing Survey) and CDDs of the form:

$$S_o = 0.944 - 1.17e^{-0.00298*CDD}$$

where S_o is "saturation" – which really is penetration for 39 US cities, which may not have reached saturation – and CDD are cooling degree days.

This simple relationship does not control for any other observables (such as income) or climate factors. Further, no standard errors are provided so it is not clear whether the relationship is statistically significant. To model consumption, the authors explain variation in state per capita electricity consumption as a proxy for city level per capita consumption using CDDs, HDDs, and wind speed. Sailor and Pavlova (2003) show that higher CDDs lead to an increased adoption and higher use of air conditioners.

Adding the extensive margin adjustment results in increases that are significant when making forecasts. Sailor and Pavlova (2003, p. 949) note that, "Based on these results, Los Angeles' per capita residential electricity consumption is projected to increase by 8% in July for a 20% increase in CDD. If the market saturation were assumed to remain constant, however, the projection would be for only a 5% increase."

Rapson (2011) estimates a discrete-time, infinite horizon dynamic consumer optimization problem. In his structural model, consumers in each period decide between buying a maximum of one unit of a durable good and the amount of household production. An interesting and important feature of his model is that households operate in an environment of uncertainty, where they do not know the efficiency of a durable good bought in a future period and may therefore wait to purchase the good until technological progress has happened. In a "first stage," he estimates derived demand for electricity from central and room air conditioners. He uses five cross sections of the Energy Information Administration's (EIA's) Residential Electricity Consumer Survey (RECS), which he matches to air-conditioner prices and efficiencies. His first-stage derived demand elasticities are consistent with more general estimates of electricity demand. For central air conditioners (CACs), he estimates that the price elasticity of derived demand is -0.170 for the whole sample and -0.068 for the sample without California. The income elasticities for both samples are 0.21. The cooling degree elasticities are near unity (0.989 for the whole sample and 0.961 without California). For room air conditioners, the price elasticity for both samples is higher (-0.34 for both samples). The cooling degree elasticities are also higher at 1.07 for all states and 1.092 for the sample without California. The income elasticities are 0.114 and 0.126, respectively. These estimation results for derived electricity demand are precisely estimated and consistent with the prior literature.

Rapson (2011) estimates unit demand elasticities with respect to electricity price, unit efficiency, and cost of the units. His estimates suggest significant responsiveness in the adoption of room air conditioners and CACs with respect to efficiency. The elasticities for CACs range from 0.7 to 1 and room air conditioners range from 0.2 to 0.3. The estimated elasticities with respect to purchase price are lower. For central air conditioning they are clustered around -0.241 and for room units they range from -0.12 to -0.13. The elasticities with respect to electricity prices are small and not statistically significant for central unit adoption (-0.024), and larger and significant for room unit adoption (-0.220; -0.35).

Rapson (2011) concludes that the timing of air-conditioner purchases responds strongly to energy-efficiency improvements and less to electricity and purchase prices. His model builds in rational expectations, which he argues “takes a step towards appropriate measurement of long run demand response to energy policy” (Rapson, 2011, p. 26). This juxtaposes findings in the literature that imply very high discount rates and findings of myopia in this context. This is an innovative structural paper that exploits the time dimension of the repeated cross sections and arrives at credible and precisely estimated coefficients for both intensive and extensive margin adjustments.

While the data for the 2011 RECS survey have not yet been released, EIA (2011a) shows a preview of the data that displays further growth in air-conditioner penetration in the United States. Figure 2 displays the most recent data by Census region. These time series show little slowdown in the growth of air-conditioner penetration. Eighty-seven percent of U.S. households had air conditioning in 2009, which is the latest year of data. EIA (2011a, EIA webpage) notes that, “wider use has coincided with much improved energy efficiency standards for AC equipment, a population shift to hotter and more humid regions, and a housing boom during which average housing sizes increased.” Figure 2 displays this growth across regions.

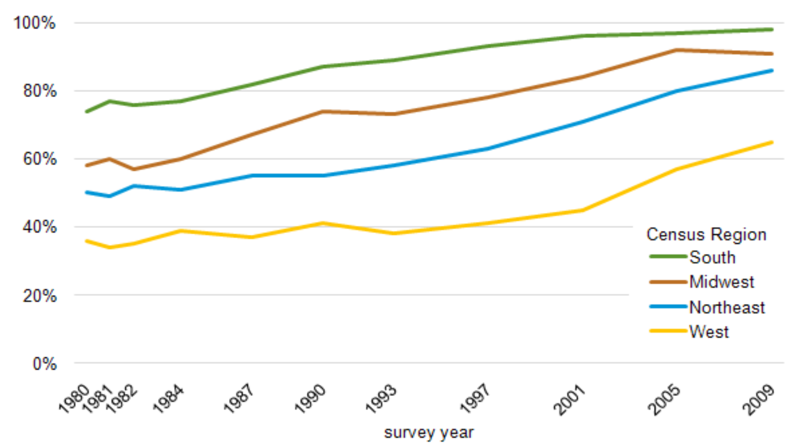

Figure 2. Share of air-conditioned homes by area.

Source: EIA, 2011a.

However, the continued growth of air-conditioner penetration questions the use of a cross section of current penetration levels as “saturation” proxies for other regions with similar climate characteristics, based on the equation by Sailor and Perova (2003) above. As shown in the next sections, cross-sectional U.S. data are used to parameterize relationships that determine climate-dependent saturation levels in other countries.

EIA (2011a) also shows that there is little variation in usage over the summer, as the percentage of households using air conditioners during the summer is between 30 and 40% – with the exception of the South where 67% of households run their air conditioners all summer. Further, as shown in Figure 3, newer homes are most likely to have central air conditioning, whereas older homes are more likely to have no air conditioning or window units as the retrofitting costs with central air conditioning are non-trivial.

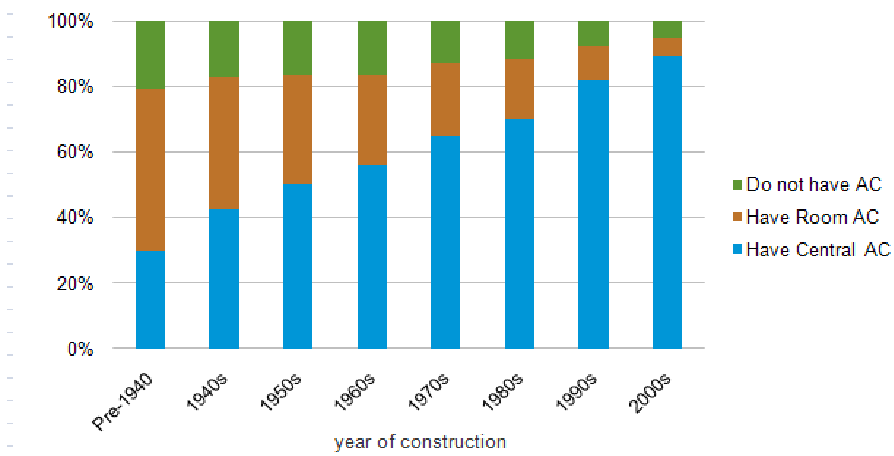

Figure 3. Central air conditioning by vintage.

Source: EIA, 2011a.

EIA (2011a) further notes that there is significant heterogeneity in the penetration and type of air conditioning units installed across the income spectrum, which is not surprising given the high cost of installing central air conditioning.

2.2 Europe

Data on air-conditioner usage and adoption in Europe are scarce and the literature we can access is minimal as a result. Multiple requests to agencies and think-tanks across Europe yielded no results. Much of the literature on changing energy demand in Europe as a consequence of climate change focuses on decreasing demand for heating instead of the increased demand for cooling. What is even more surprising is the lack of publicly available data and studies at the member country level. Given the predicted shifts in climate for European Union (EU) member countries and the relatively high incomes, a better understanding of intra-European adoption patterns is important to better project future electricity demand in the EU.

The most informative report is the Directorate-General for Mobility and Transport (European Commission) study (DGTE, 2003), which overviews the penetration of CACs and their efficiencies across EU member states. CACs here are defined as air-conditioning systems with more than 12 kW of cooling capacity, which does not include smaller room type air conditioners. The report indicates that the area cooled per inhabitant is expected to rise rapidly from $3m^2$ per inhabitant in 2000 to $5m^2$ per inhabitant by 2010. Figure 4 indicates the growth in CACs in the EU over the recent past, which almost quintupled in a 20-year period.

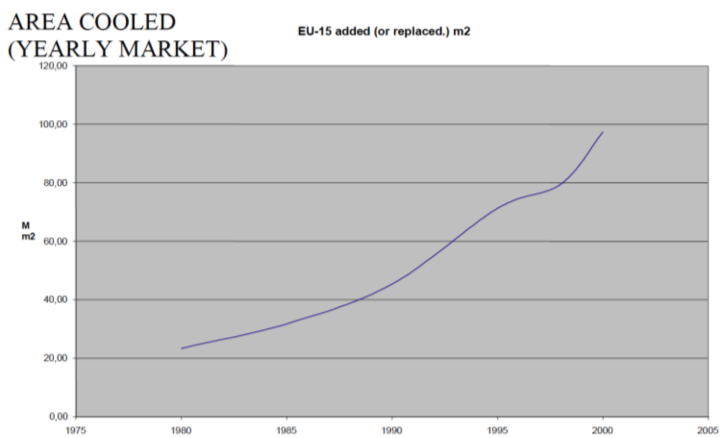

Figure 4. Area cooled by CACs in Europe.

Source: DGTE, 2003.

The rapid growth is driven by the expansion of cooled floor area in Italy and Spain, which now are responsible for more than 50% of the cooled floor area. If one normalizes cooled area by population, the distribution of cooled square meters per person is highly correlated with summer temperatures. Figure 5 only displays the cross-sectional variation, when in fact how these measures have developed over time would enable us to better understand the drivers of these series – especially the relative roles of rising incomes versus changing temperatures.

Aebischer et al. (2007) provide another study that predicts energy demand for Europe under climate change. The paper is not very clear on how predictions are calculated and focuses on the tradeoff between heating and cooling demand thereafter.

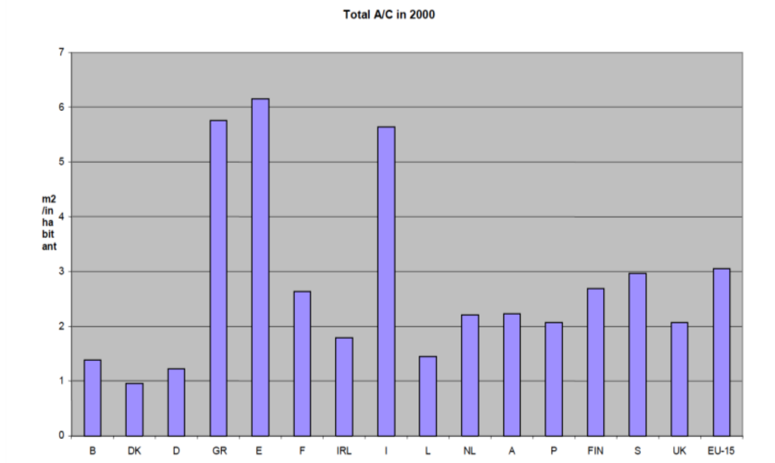

Figure 5. Per capita cooled area, Europe.

Source: DGTE, 2003.

Given the climate heterogeneity in Europe and predicted warming throughout the continent, combined with the member countries' relatively high incomes, further studies of changing air-conditioner penetration and collection of data could provide important insights into the future of European energy demand. A concerted effort, if not already underway, to collect and analyze data similar to what Rapson (2011) or Biddle (2008) did would be insightful, given the tremendous degree of heterogeneity in weather, electricity prices, and incomes across the EU member states. While the penetration of air conditioners in central and northern Europe is very small, under climate change these rates can potentially grow rapidly with significant impacts on electricity consumption and the load profile. Given a shift away from nuclear power for base load, for example, in Germany, these shifts could have significant impacts on load profiles and the ability of generators to meet peak demand.

2.3 Developing Countries

McNeil and Letschert (2005, 2010) and Letschert and McNeil(2009) provide a model of adoption of air conditioners and appliances using cross-country data. They incorporate the fact that saturation levels are climate dependent, which is the idea raised in Sailor and Pavlova (2003). While they do not adequately discuss their sample or the time period covered, they appear to collect a cross section of data on adoption rates by country from a number of micro level surveys – most of which are in the World Bank Living Standards Measurement Study (LSMS) database for various years (mostly late 1990s and early 2000s). McNeil and Letschert (2008) discuss these data in more detail, yet the working paper is not referenced in the 2010 paper. In a first step, they estimate a relationship between saturation (which they call "Climate Maximum") and CDDs for 39 U.S. cities. Their estimated coefficients differ slightly from those in Sailor and Perova (2003):

$$S_o = 1.0 - 0.949e^{-0.00187*CDD}$$

Figure 6 displays the original fit of the relationship by Sailor and Perova (2003) as well as the corrected fit in McNeil and Letschert (2010). The corrected curves are slightly flatter.

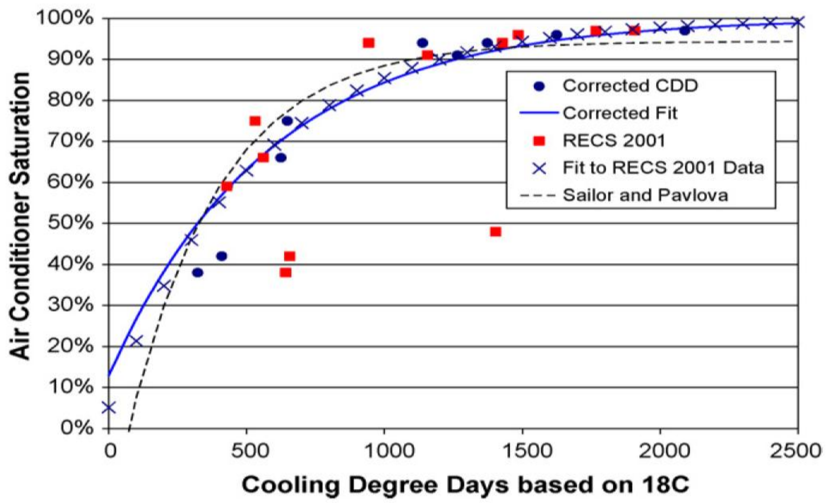

Figure 6. Air-conditioner saturation across U.S. cities.

Source: McNeil and Letschert, 2010.

McNeil and Letschert (2010)then use this estimated relationship to estimate a predicted saturation level based on CDDs for a given location. For developing country locations in their sample, air-conditioner saturation is assumed to approach this frontier but not exceed it. They then model diffusion of air conditioners as a function of income, conditional on a location's Climate Maximum, which is a function of CDD. The diffusion equation for air conditioners is:

$$\ln\left(\frac{\text{Climate Maximum}_i}{Diff_i} - 1\right) = \ln\gamma + \beta_{inc}\text{Income}_i + \varepsilon_i$$

What is different in this equation is that Climate Maximum is the cooling degree dependent saturation level based on the cross section of U.S. cities discussed above. For other appliances such as refrigerators, a common value (e.g., 1 per household) is used. If the Climate Maximum for a given country is 1 and the saturation is 1, penetration is therefore 100%. If the Climate

Maximum is 0.1 and the saturation is 0.1, penetration (or in their language "availability") is also 100%. The estimated relationship based on 24 cross-sectional observations between per capita income and air conditioner "availability" is given in Figure 7 (the y-axis measures availability, which is diffusion divided by the Climate Maximum and which is capped at 100%):

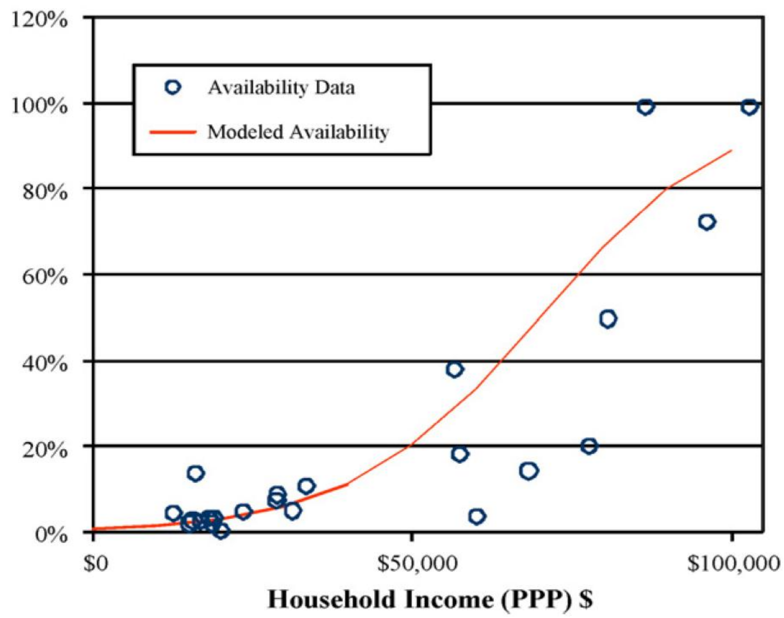

Figure 7. Predicted air-conditioner penetration across countries.

Source: McNeil and Letschert, 2010.

McNeil and Letschert (2010) explain that 60% of the variation in the transformed dependent variable and the error distribution is less than 30% for all observations. What is noteworthy about the estimated adoption curve is that the penetration rates are very low and clustered around zero for a number of countries. At income levels of $25,000 the adoption rates seem to rise drastically. While the modeling approach here is appealing and the data collection effort is impressive, this is essentially a cross-sectional regression that cannot meaningfully control for confounding factors. Using repeated cross sections or panel data on this model would allow one to separate out unobservables via a two-way fixed or random-effects strategy. We do just that for the case of China in Section 4.

Isaac and van Vuuren (2009) build on the model by McNeil and Letschert (2010), but in addition endogenize the unit energy consumption (UEC) as a function of income, which allows for income-dependent energy efficiency of air conditioners. They then predict penetration rates based on CDD and income, which allows them to build regional predictions. They show that their model can predict U.S. penetration very well, but is off by 30% for Japan.

Akpinar-Ferrand and Singh (2010) look at air-conditioning demand for India. The authors use a combination of air-conditioner ownership data from the National Sample Survey (NSS) 55 survey (2001) and sales data from industry sources. They follow the same approach as Isaac and van Vuuren (2009) described above. Figure 8 displays an astonishing rate of sales of air-conditioning units in India:

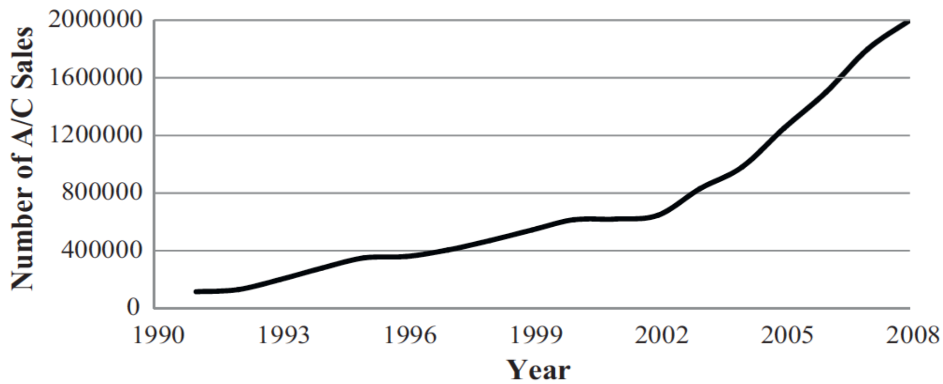

Figure 8. Air-conditioning unit sales in India.

Source: Akpinar-Ferrand and Singh, 2010.

The combination of rapidly rising incomes and a hot, and in many cases humid, climate has led to very fast growth in sales in urban areas with a relatively reliable electricity supply. Rural area adoption has lagged as only 44% of rural households have access to electricity. Akpinar-Ferrand and Singh (2010) predict a rapid rise in the penetration rates of air conditioners over the next century (Figure 9).

2.4 "Global"

While the number of global models addressing a changing global energy demand under climate change is very broad (e.g., IPCC, 2000), we focus on three papers here, which are cited as important input to one of the major integrated assessment models, the FUND model. Downing et al. (1996a) provide an executive summary of the Downing et al. (1996b) study. Many costs of damages from climate change assessed in this study rely on non-market valuation, yet the energy component relies on direct means of valuation.

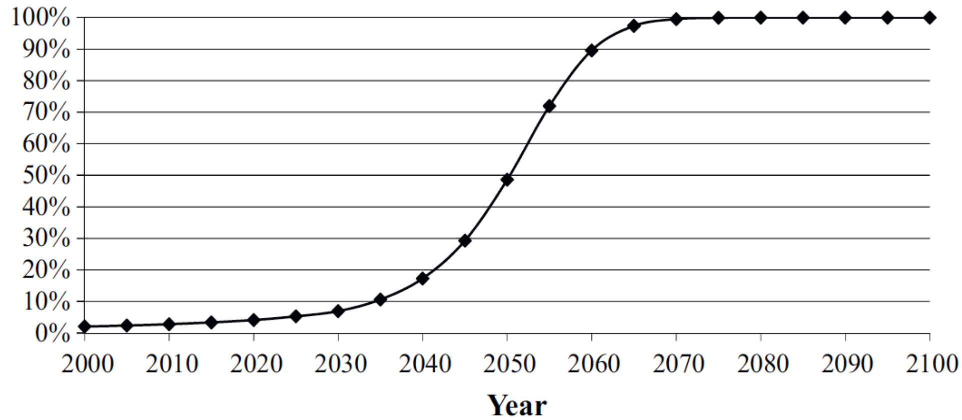

Figure 9. Air-conditioner penetration in India.

Source: Akpinar-Ferrand and Singh, 2010.

The underlying major assumption in this global study is that “within the major regions of the world, energy use for each activity is apportioned according to the product of GNP and degree days.”(Downing, 1996b, p. 21) Therefore, hot and rich regions use much energy for each activity and poor and cold regions use less. The intuition is that temperature and income, the main drivers of adoption, are proportional to use. It is important to note, however, that the most interesting regions to study in terms of adoption are poor and hot regions. Second, “space heating demand is specified as a simple linear function of degree days with base 15 degrees” (Downing, 1996b, p. 21), which makes an important and potentially not correct functional form assumption. Finally, “the market penetration of space cooling equipment and the energy use of that equipment are linear functions of CDDs with a base 20°C, with a minimum energy use corresponding to 30 annual degree days” (Downing, 1996b, p. 22), which is another functional form assumption that has not been verified empirically.

The two scenarios giving rise to energy consumption impacts form increased cooling and decreased heating in the paper rely on energy use scenarios to the year 2100 as provided by a study at the Stockholm Energy Institute (SEI, 1993), which contains detailed energy use data. This study makes a number of significant crude assumptions at the macro level, which have not been verified empirically.

While the manuscript does not provide a sufficient description of the model employed to arrive at damages, it ignores the effect of energy prices (“price effects have been neglected,” SEI, 1993, p. 22). Further, the model makes assumptions about a key parameter, the “autonomous energy efficiency improvement” (AEEI), which is a key exogenous driver of demand. The authors note that "over a long period, even very modest differences in the size of this parameter can have a significant effect (Ekins, 1995), far outweighing likely price effects" (Downing, 1996b, p. 24). The authors use a back-of-the-envelope calculation for the AEEI for the United Kingdom over the period 1920–1985 of 0.5%/year and conclude that the AEEI for space heating for the IS92a scenario should be less than 0.5%/year. For the IS92d scenario the authors assume an AEEI of 0.8%/year. They then simply assume an AEEI for the IS92a scenario of 0.3% without much justification. For space cooling, the authors calculate/approximate an AEEI of 1.2%/year for the IS92d scenario and a negative -0.3%/year AEEI for the IS92a scenario. This would lead to a five-fold increase in space cooling in the IS92a scenario over the IS92d scenario simply due to this parameter choice.

It is not surprising that the demand for space cooling grows by a factor of 17 by the end of century for the IS92a scenario and a factor 2.5 for the IS92d scenario. This also results in massive differences in estimated cooling costs.

One should further note that the Greenpeace-funded SEI (1993) report makes very strong assumptions about appliance saturation. For example, it assumes that saturation in the United States is 100% and simply scales back the energy intensity of the air conditioners to match the observed consumption. This has, of course, important implications for the impact of future electricity consumption from more adoption versus higher usage. It is not clear from the document how exactly the adoption decision is separated from the usage decision. The micro-level studies discussed above provide a much more detailed and by now geographically broad look at these relationships and would allow for a better parameterization of new energy models.

In summary, many of the global models make very crude assumptions about the macro level drivers of energy use from heating and cooling. This is in many cases necessary as energy is just one of many sectors. A more careful parameterization based on econometric studies of the intensive and extensive margin adjustments in cooling demand would likely lead to more realistic and less variable predictions of future damages from increased cooling demand. Further, one should note that cooling is a major strategy for adaptation, which will likely offset major health impact driven damages as well. The linkage between these two important dimensions in studying climate change impacts should be carefully considered in the benefit-cost context.

3. Available Data

Table 4 lists the data sources used in the studies discussed above and provides links to the webpages where the data and detailed information regarding the datasets can be obtained.

Table 4. Available data sources

Name	Aggregation	Spatial coverage	Temporal coverage	Frequency	Source
United States					
Energy Consumption Survey	Household	United States	2009, 2005, 2001, 1997, 1993	~ 5 years	EIA, 2011b
Regional Appliance Profiles	Census region	United States	1980–2001	~ 5 years	EIA, 2011c
IPUMS	PUMS	United States.	1960, 1970, 1980	10 years	IPUMS, 2011
Residential Appliance Saturation Survey	Household	California	2009, 2003	~ 5 years	CEC, 2011
American Housing Survey	Household	United States	1973–2009	~2 years	U.S. Census Bureau, 2011
AHRI	Census region	United States	1978–2005	Biannual	AHRI, 2011
International					
National Bureau of Statistics China	Province	China	1995–2009	Annual	National Bureau of Statistics of China
LSMS	Household	See Table 5	Varied	Annual	World Bank, 2011
NSS	Household	India	Varied	Annual	NSS, 2011

AHRI: Air-Conditioning, Heating, and Refrigeration Institute.
IPUMS: Integrated Public Use Microdata Series Census Data.

McNeil and Letschert (2008) list the LSMS surveys conducted by the World Bank, which contain information on appliance adoption at the household level. There are many countries with such micro surveys, which may offer themselves the possibility of micro-econometric examination. For most countries there is just a single cross-sectional sample. Examination of the survey document for Nicaragua, however, shows that for the 2001 and 2005 rounds a question about air conditioning was asked. The earlier years do not appear to contain questions about air conditioning in the asset holding section. Further examination of the country-specific survey instruments on the World Bank LSMS website (e.g., for the 1997 Panama survey), which are provided in the local language without English translation in many cases, may yield more countries with repeated questions about air-conditioner ownership, which would enable a quasi-panel-type econometric research design.

Table 5. LSMS surveys with air conditioner data

Country	Year of survey	GDP/mo ($)	CDD	Saturation
Nicaragua	2001	$1,122	1533	0.50%
Albania	2002	$1,093	3342	2.10%
India	1999	$1,093	3120	2.10%
Sri Lanka	1999	$1,312	2319	2.10%
Indonesia	1997	$1,216	466	2.70%
Honduras	2001	$1,108	3187	3.20%
Egypt	2003	$1,293	3249	3.40%
Ghana	1997	$950	1265	4.50%
Philippines	2003	$1,567	3559	5.00%
Paraguay	1992	$2,531	1611	5.00%
Brazil	1996	$2,062	221	7.20%
Panama	2000	$2,094	3001	8.80%
Thailand	2000	$2,353	2742	10.80%
China	2000	$1,102	881	12.00%
South Africa	2002	$4,472	739	15.00%
Mexico	2003	$3,772	3280	17.40%
Syria	2002	$1,837	723	17.40%
Spain	2001	$4,833	734	29.00%
Australia	1998	$5,814	542	40.00%
Italy	1996	$4,856	365	40.00%
Canada	2003	$5,927	263	41.70%
Singapore	2003	$6,505	850	72.00%
United States	2001	$7,028	3280	72.00%
South Korea	2000	$3,616	974	85.00%

GDP: gross domestic product.
Source: McNeil and Letschert, 2007.

4. Explaining the Adoption of Air Conditioners in China's Urban and Rural Households

This section explores the diffusion of air-conditioning units for a rapidly developing economy – the People's Republic of China. As Fridley et al. (2001) predicted a decade ago, the market for air conditioners in China has experienced explosive growth. A back-of-the-envelope calculation based on the publicly available data in the China Statistical Yearbook (National Bureau of Statistics of China, 2010) suggests that each urban household owns 1.07 air-conditioning units and each rural household owns 0.12 air-conditioning units. This suggests that in 2009 the national average was 0.64 air-conditioning units per household or a total of 252 million installed air conditioners. Both statistics display a positive trend. The industry also grew at a rapid pace. Between 1990 and 1998 Chinese production of air conditioners went from below 0.5 million units per year to more than 11.5 million units per year (Fridley et al., 2001). The most telling prediction in their paper is the statement," in some middle and upper class households, air conditioner ownership has evolved from one air conditioner per household to on air conditioner per room. This trend is expected to continue"(Fridley et al., 2001, p. 4). The vast majority of air-conditioner sales are room air conditioners (split design), with the share of window units decreasing.

The Department of Urban Social and Economic Survey of the National Bureau of Statistics conducts an annual rural and urban household survey. The urban survey samples 60,000 households nationwide and the rural survey samples 70,000 households nationwide.[1] One section of the lengthy survey collects data on asset holdings by households. We therefore observe total asset holdings by rural/urban location of households for 30 province-level entities. We did not observe the actual survey data, which would allow for a much richer econometric exercise than we are about to conduct. Another drawback is that we did not observe any information about the types of air conditioners people own. The question simply asks about the number of air-conditioning units for a given household. This has the advantage that our statistics can allow for penetration rates greater than 1 if a household has multiple air conditioners. We, however, cannot model a shift from window units to split design and central units.

Aggregate data at the province level have been published since 1995. Figure 10 displays the number of air conditioners per 100 households for 1995 and 2009 as bars. The rapid growth in the number of installed units can be detected by the difference in the size of the light and dark grey bars for each province. The figure shows that there is significant cross-sectional as well as time-series variation in these data. Guangdong (hot and relatively high income) has a penetration of almost two air conditioners per urban household, while Tibet (cooler and poor) has almost no air conditioners.

1. More detail on the survey is provided in Appendix B.

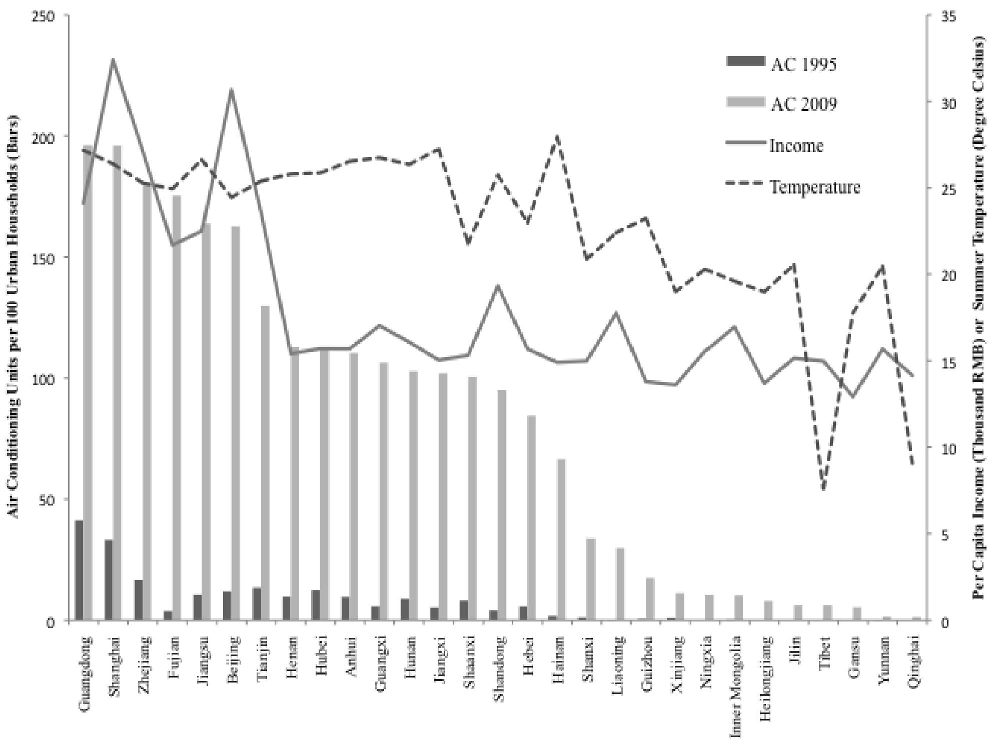

Figure 10. China's urban household air-conditioner penetration, income, and summer temperatures.

Figure 11 displays the same information as Figure 10, yet for rural households. In 1995 almost no provinces reported air conditioners in rural households. Therefore, report penetration is provided for 2000 and 2009. The same correlation among weather, income, and penetration can be seen for rural areas as in the urban areas (Figure 10), yet the penetration rates are much lower in rural than in urban areas.

As the literature review above suggests, the two main driving factors of penetration and ultimately saturation are climate/weather and per capita income. We do not have province-level estimates of HDDs or CDDs, which require temperature at the daily resolution, which is not easily available for China. For weather we have therefore obtained the monthly temperature and rainfall data from Matsuura and Willmott (2011). We mapped the 0.25×0.25 degree grids to provincial boundaries via ESRI's ArcView and calculated mean monthly temperatures and precipitation for each province by calculating a simple mean of grid cells whose centroid lay within the provincial boundary. Figures 10 and 11 show the provincial mean summer temperature (average of June, July, and August) from 1961 to 1990 for each province as a grey dashed line. There is a clear negative correlation between temperature and penetration.

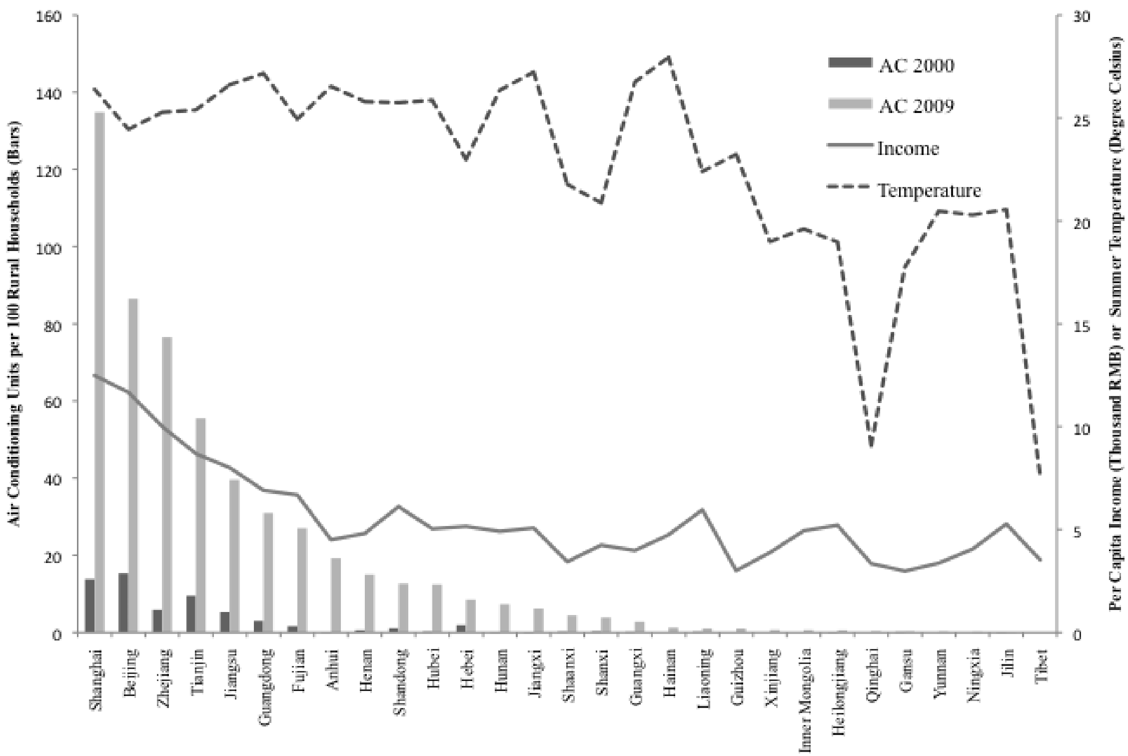

Figure 11. China's rural household air conditioner penetration, income, and summer temperatures.

For income, we recorded per capita annual personal income for each province from the China Statistical Yearbooks (National Bureau of Statistics of China, 1996–2010), which has two advantages. First, per capita personal income is arguably a better measure of the funds available to the average citizen in a province than per capita GDP given the large amount of transfers and interprovince trade. Second, it is reported separately for rural and urban areas each year for each province. The per capita figures were deflated using the national consumer price index (CPI), so all numbers are in 2008 Renminbi (RMB). There is a clear positive correlation among income, temperature, and penetration of air conditioners, as can be seen from Figures 10 and 11. The simple correlation coefficient between urban penetration (2009) and average summer temperature between 1961 and 1990 is 0.69 and the correlation coefficient between penetration and per capita income is 0.78, suggesting that hot urban areas with a hotter summer climate have a higher penetration of air conditioners.

The panel nature of the dataset provides a new opportunity to identify the effect of income and weather on penetration of air conditioners. Instead of using an additive linear specification in levels or logs, it is common to use a logistic specification in the adoption literature, which imposes an "S-shaped" adoption curve over time. This diffusion equation is commonly specified as follows (e.g., McNeil and Letschert, 2010):

$$\text{Diff}_i = \frac{\alpha_i}{1+\gamma\left(\beta X_i\right)}$$

where Diff_i is the penetration rate of an appliance in state or country *i*, α_i is the saturation level of the appliance for state or country *i*, and X_i is a variable thought to increase (or decrease) the adoption rate in country *i*. In the case of air conditioners the saturation level is usually not constant across countries as the saturation level may differ across space depending on local climate. As discussed above, McNeil and Letschert (2010) assume that countries will approach saturation at U.S. levels and use the RECS penetration as the saturation levels to set alpha. They estimate an equation of the form:

$$\text{Diff}_i = \frac{\alpha\left(CDD_i\right)}{1+\gamma\left(\beta Inc_i\right)}$$

where α_i depends solely on the CDDs in area *i* and the only factor driving adoption is income (Inc_i). Climate (CDD_i) therefore only affects the saturation level, not the speed of adoption through an additional term in the brackets in the denominator. One could of course also estimate this relationship using a single time-series for a country or state, by replacing the subscript *i* with a subscript *t*. In fact, Letschert et al. (2010) do this by using a national time series for Chinese air conditioners. Their report also includes a year dummy variable in addition to per capita income, which in a univariate time series would lead to an unidentified model. Due to this specification error, we do not discuss this working paper any further and instead focus on how we can use their specification by exploiting the cross-section and time-series variation in the panel data we have obtained.

If we extend the specification to allow for panel data, the equation reads:

$$\text{Diff}_{ijt} = \frac{\alpha}{1+\gamma_i\left(\beta X_{ijt}\right)},$$

where each observation is now for province *i* and year *t* and is estimated separately for whether *j* is rural or urban. Rearranging, taking logs and adding a well behaved i.i.d. error term we get:

$$\ln\left(\frac{\alpha}{Diff_{ijt}}-1\right) = \ln\left(\gamma_i\right) + \beta X_{ijt} + \varepsilon_{ijt}$$

In this equation, the saturation level α_i is restricted to be identical for each province. γ, which in the specification above, varies by province, governs how far to the right the S-curve is shifted and the vector of coefficients on the remaining right-hand side variables, β, governs the slope of the S-curve. As we have 29 provinces in our sample,[2] we could of course estimate 29 different regressions to recover the parameters of interest (γ, β) separately for each province by rural status. This would provide province-specific estimates of (γ, β) by rural status. This would not allow us, however, to differentiate between the impact of observable income from other confounders, which we do not observe. These are, as we have learned from the literature review above, prices of air conditioners, their efficiencies, and the price of electricity. If these trends are correlated with income, the resulting coefficient on income would be biased. Due to the panel nature of the data, we can estimate a single equation by rural status, which allows for the flexibility of province specific γ and year-specific confounders, which affect all provinces and a pooled coefficient on per capita income. This equation becomes:

$$\ln\left(\frac{\alpha}{Diff_{ijt}}-1\right)=\delta_i+\varphi_t+\beta_{inc}Inc_{ijt}+\varepsilon_{ijt}$$

where δ_i is a province-specific ln $\gamma\varphi_t$ are year fixed effects, which control for shocks unobservable to the econometrician as discussed above. The advantage here is that the province and year fixed effects control for unobservables that are time invariant by province and time variant but common to all provinces. The panel specification, however, assumes a common slope on the income variable. One question, which is largely unaddressed in the literature, is how current or recent weather shocks affect air-conditioner adoption patterns. We therefore will also estimate equations as follows:

$$\ln\left(\frac{\alpha}{Diff_{ijt}}-1\right)=\delta_i+\varphi_t+\beta_{inc}Inc_{ijt}+\sum_{r=0}^{R}\beta_{it-r}T_{it-r}+\varepsilon_{ijt}$$

where *T* is the average temperature in province *i* in year *t*. One could easily imagine that a hot summer will result in increased air-conditioner purchases the following summer. We therefore control for current and lagged temperature. We include up to R = 4 lags.

Our data differ from those of McNeil and Letschert (2010) in that we observe penetration rates that are significantly higher than one per household in some locations as we have counts of the total number of air conditioners per household for a province. Further, we do not observe CDDs, but mean monthly temperature. We therefore cannot use their relationship for setting α without

2. We drop Sichuan and Chongquing, which were merged into a single unit halfway through our sample. Lacking the appropriate weights for the air-conditioner data, we dropped both from the sample.

redoing the estimation on the RECS data using counts and average temperatures. This is beyond the scope and time allowance for this project. We therefore follow two strategies. First, we estimate the univariate regressions at the province level above varying α from the current level to three air conditioners per household and selecting the "optimal" α by minimizing the sample mean squared error (MSE). As described above, this leaves us with 29 estimated α_i, γ, and $\beta_{inc.}$ Table 6 displays the estimated coefficients for each province.

A few things are worth noting in Table 6. The province regressions are listed in descending order according to 2009 urban air-conditioner penetration. First, it is not surprising given the logistic functional form that the MSE minimizing α is just outside the current maximum penetration. Second, income is statistically significant at the 1% level for all provinces. Third, the beta coefficients are negatively correlated with 2009 income, suggesting that poorer provinces have steeper diffusion curves, which is also intuitive. Finally, the 2009 income is positively and significantly correlated with gamma, suggesting that poorer provinces' adoption curves are shifted further to the right, suggesting later adoption. The latter two observations are clearly not causal but consistent with economic intuition. Next, we experimented with including different measures of summer temperature in the adoption curves. Specifically we included current summer temperature and lagged summer temperature, both jointly and separately in the regression equation. Lagged temperature is only marginally significant in the regressions for Tianjin, Jilin, and Yunnan. Current summer temperature is only marginally significant in the regressions for Beijing, Tianjin, Hebei, and Tibet. This may be an issue of power in the regressions and will be revisited in the panel regressions text.

One aspect of the province-specific estimation with province varying is the ability to forecast, given that the saturation parameter for all provinces is so close to 2009 levels. We address this point in a set of panel regressions at the cost of fixing at a somewhat arbitrarily chosen level of 200 per 100 households (which is near the highest number observed in the data). We first run a pooled regression without fixed effects and simply control for income. Next we run a panel fixed effects regression with the province and without the year fixed effects. In the cross-sectional regressions discussed in the literature review above, one would be worried about the effects of unobservable time-invariant differences, which may be correlated with income on adoption. Adding the province fixed effects overcomes this concern. Next we add year fixed effects. The concern here is that the only time-varying control in the univariate regressions is per capita income. If per capita income is correlated with factors we cannot explicitly control for, we will wrongly attribute the effects of these confounders (e.g., electricity prices, air-conditioner pricing) to income. The panel data allow us to control for both time invariant unobservables at the province level as well as year-to-year shocks. We then run five additional regressions where we control for current temperature and then sequentially add lags of temperature up to the fourth lag.

Table 6. Province specific diffusion functions without weather

Name	Guangdong	Shanghai	Zhejiang	Fujian	Jiangsu	Beijing	Tianjin	Henan	Hubei	Anhui
Province ID	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
α_i	200%	200%	185%	180%	165%	165%	130%	115%	115%	115%
AC Urban (2009)	188%	191%	171%	164%	155%	152%	125%	103%	106%	108%
β_{inc}	-0.303***	-0.214***	-0.243***	-0.406***	-0.338***	-0.276***	-0.353***	-0.496***	-0.593***	-0.522***
	(0.0208)	(0.0117)	(0.0164)	(0.0358)	(0.0246)	(0.0250)	(0.0306)	(0.0420)	(0.0546)	(0.0355)
$\ln(\gamma)$	3.755***	3.136***	3.645***	5.123***	4.011***	4.034***	3.807***	3.863***	4.599***	4.480***
	(0.307)	(0.215)	(0.257)	(0.433)	(0.292)	(0.427)	(0.388)	(0.348)	(0.479)	(0.304)
Observations	14	14	14	14	14	14	14	14	14	14
R-squared	0.946	0.965	0.948	0.915	0.940	0.911	0.917	0.921	0.908	0.947

Name	Guangxi	Hunan	Jiangxi	Shaanxi	Shandong	Hebei	Hainan	Shanxi	Liaoning	Guizhou
Province ID	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
α_i	110%	105%	105%	105%	100%	90%	70%	35%	30%	20%
AC Urban (2009)	101%	97%	96%	100%	90%	82%	65%	33%	27%	16%
β_{inc}	-0.522***	-0.558***	-0.549***	-0.516***	-0.409***	-0.663***	-0.625***	-0.598***	-0.529***	-0.633***
	(0.0504)	(0.0451)	(0.0294)	(0.0265)	(0.0367)	(0.0718)	(0.0885)	(0.0408)	(0.0884)	(0.0678)
$\ln(\gamma)$	5.332***	5.079***	4.865***	4.283***	4.471***	5.373***	5.879***	5.400***	6.085***	6.143***
	(0.477)	(0.423)	(0.241)	(0.217)	(0.387)	(0.634)	(0.761)	(0.344)	(0.807)	(0.532)
Observations	14	14	14	14	14	14	14	14	14	14
R-squared	0.899	0.927	0.967	0.969	0.912	0.877	0.806	0.947	0.749	0.879

Name	Xinjiang	Ningxia	ner Mongol	Heilongjiang	Jilin	Tibet	Gansu	Yunnan	Qinghai
Province ID	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)
α_i	15%	15%	15%	10%	10%	10%	10%	5%	5%
AC Urban (2009)	11%	8%	8%	8%	6%	6%	6%	1%	2%
β_{inc}	-0.423***	-0.468***	-0.476***	-0.661***	-0.325***	-0.205**	-0.498***	-0.403***	-0.385**
	(0.0537)	(0.0611)	(0.0582)	(0.0847)	(0.0599)	(0.0711)	(0.0765)	(0.0970)	(0.115)
$\ln(\gamma)$	4.438***	5.617***	5.730***	6.012***	3.592***	2.711***	5.537***	6.696***	5.668***
	(0.452)	(0.525)	(0.505)	(0.678)	(0.555)	(0.764)	(0.641)	(0.905)	(1.063)
Observations	14	12	14	13	10	10	11	14	9
R-squared	0.838	0.855	0.848	0.847	0.786	0.508	0.825	0.590	0.616

Column (1) in Table 7 shows the pooled regression with a coefficient on per capita income of -0.338. When controlling for province-specific fixed effects, the coefficient on income moves to -0.287, which is statistically different from zero and -0.338 at the 1% level. When controlling for year fixed effects in model (3), the income effect is cut by two-thirds to -0.0953. This estimate is again significantly different from zero and -0.287 at the 1% level. The first three sets of regression results provide three significant pieces of insight. First, province level unobservables positively correlated with income appear to be somewhat significant drivers of adoption. Failing to control for them in our case leads to overestimation of the income effect. More importantly, however, time shocks (e.g., prices of air conditioner units, electricity prices, and efficiency

Table 7. Panel data estimation results urban areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
b_{inc}	-0.338***	-0.287***	-0.0945***	-0.0953***	-0.0885***	-0.0718**	-0.0699**	-0.0760**
	(0.0269)	(0.0185)	(0.0270)	(0.0280)	(0.0301)	(0.0272)	(0.0302)	(0.0350)
$Temp_t$				0.0176	0.0395	0.0375	0.0102	0.0388
				(0.0482)	(0.0488)	(0.0465)	(0.0417)	(0.0482)
$Temp_{t-1}$					-0.114**	-0.0936**	-0.0960**	-0.115***
					(0.0422)	(0.0391)	(0.0409)	(0.0400)
$Temp_{t-2}$						-0.101***	-0.0996***	-0.0971***
						(0.0304)	(0.0292)	(0.0336)
$Temp_{t-3}$							-0.0857**	-0.0801**
							(0.0322)	(0.0300)
$Temp_{t-4}$								-0.0964***
								(0.0296)
Constant	5.664***	5.167***	5.067***	4.666***	4.077**	5.791***	10.24***	10.34***
	(0.492)	(0.180)	(0.197)	(1.045)	(1.630)	(1.874)	(2.364)	(2.622)
Province FEs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Alpha	200	200	200	200	200	200	200	200
Observations	387	387	387	387	364	338	312	287
R-squared	0.443	0.747	0.895	0.895	0.886	0.899	0.897	0.888
Provinces	29	29	29	29	29	29	29	29

FE: fixed effects.

Note: Standard errors are clustered by province. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

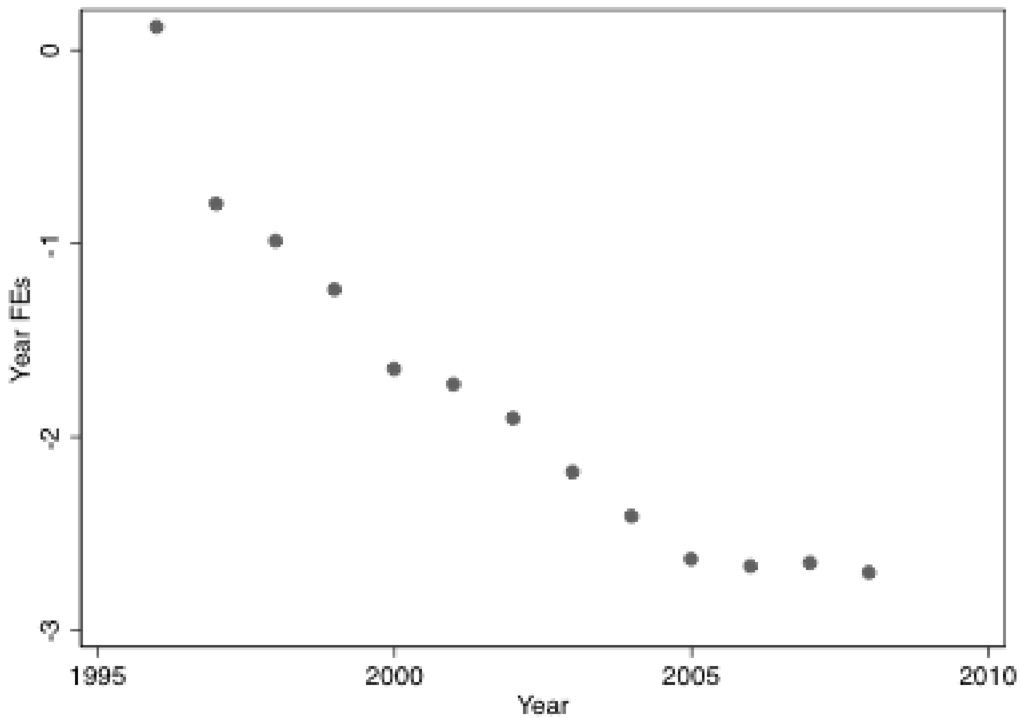

Figure 12. Year fixed effects [Model (3), Table 7].

improvements) that are correlated with income will lead to a significant overestimation of the income effect. If one cannot explicitly control for these effects, cross-sectional or univariate time-series approaches will likely provide biased coefficient estimates. The magnitude in the drop of the coefficient on income is consistent with the findings in Rapson (2011). From a forecasting perspective, however, models including time-fixed effects lead to a complication. When using such a model to forecast out of sample, one would need to forecast the evolution of the fixed effects (see Schmalensee et al., 1998, for a solution to this problem). The fixed effects here display a clear trend, as shown in Figure 12, which would have to be forecast out of sample in addition to per capita income.

Model (4) adds contemporaneous summer mean temperature, which is not significantly different from zero. Model (5) adds a single lag of temperature, which is statistically different from zero and has the correct sign. Higher temperatures in the summer will lead to higher adoption the following summer. This is consistent with a behavioral pattern where households save after a hot summer in order to purchase an air-conditioning unit for the next summer. The fact that this coefficient is significant in the panel regressions and not in the univariate regressions may be due to the additional degrees of freedom in the panel regression. We sequentially add more lags of temperature; the coefficients are significant and do not show much of a decrease the further back in time we go. What this implies is that people buy more air conditioners one, two, three, or four years after a hot summer, which is consistent with a pattern of saving to invest in this technology. It may take different households different periods of time to save enough for an air conditioner, even though this model cannot even come close to examining the mechanisms in this context. In Appendix A, Figures A.1–A.5 display the data and four fitted models. The models are surprisingly similar in overall MSE performance and prediction in the sample.

Air-conditioner penetration is much lower in rural areas than in urban areas. The national average in 2009 was 12.23 air conditioners per 100 households. This number is even smaller in per capita terms as the average household size in urban areas is 2.89 versus 3.98 in rural areas. The slow adoption over the sample period and low penetration makes it difficult to extract a signal from this series. The estimation results in Table 8 reflect this. After controlling for province and year-fixed effects, the income variable is a statistical zero. The weather variables, however, are significant and sizable. Current and lagged weather lead to more rapid adoption. The effect is almost twice that of the weather effect in urban areas.

In order to check whether what we have estimated so far is a spurious relationship, we estimate a model for urban and rural areas separately using a durable good whose adoption should not be weather dependent. Table 9 lists the results for this falsification test with cameras and washers. In none of the models does lagged temperature come in significant as expected. This finding holds when we include additional lags.

5. Comparison of U.S. and China

A direct comparison of the United States to China would require comparable data, which we cannot access. However, we can use the RECS data published by the EIA to draw some comparisons. China's total population in 2009 is estimated at 1.344 billion. Forty-seven percent of China's population is characterized as living in urban areas. The average household size in urban areas is estimated to be 2.89 people, while the household size in rural areas is 3.98 people. The number of air-conditioning units in urban households is 1.0684 on average, while the number of air-conditioning units in rural households is 0.1223 on average. The weighted average for 2009 is therefore 0.6386 air conditioners per household nationally – and rising. As EIA (2011a, EIA webpage) states, "As recently as 1993, only 68% of all [United States] occupied housing units had AC." This puts current day China near what the United States was in 1993.

Table 8. Panel data estimation results in rural areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
b_{inc}	-0.953***	-0.825***	-0.0115	0.0116	0.0504	0.0758	0.0967	0.105
	(0.0673)	(0.118)	(0.185)	(0.174)	(0.167)	(0.168)	(0.171)	(0.175)
$Temp_t$				-0.218***	-0.149**	-0.201***	-0.184***	-0.179***
				(0.0694)	(0.0582)	(0.0646)	(0.0608)	(0.0611)
$Temp_{t-1}$					-0.243**	-0.212*	-0.225*	-0.231**
					(0.115)	(0.111)	(0.110)	(0.112)
$Temp_{t-2}$						-0.236***	-0.224***	-0.221***
						(0.0779)	(0.0764)	(0.0768)
$Temp_{t-3}$							-0.185**	-0.192**
							(0.0807)	(0.0825)
$Temp_{t-4}$								-0.0871*
								(0.0456)
Constant	8.514***	8.007***	3.707***	8.761***	12.83***	18.96***	23.00***	25.23***
	(0.354)	(0.468)	(1.067)	(1.793)	(2.606)	(3.718)	(5.034)	(5.678)
Province FEs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Alpha	200	200	200	200	200	200	200	200
Observations	224	224	224	224	224	224	223	222
R-squared	0.689	0.521	0.684	0.691	0.703	0.715	0.723	0.725
Provinces	29	29	29	29	29	29	29	28

Note: Standard errors are clustered by province. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Falsification tests

	Rural		Urban	
Asset	**Washers**	**Cameras**	**Washers**	**Cameras**
b_{inc}	-0.0185	-0.0615***	0.139**	-0.0405
	(0.0125)	(0.0194)	(0.0540)	(0.0634)
$Temp_{t-1}$	-0.00390	-0.000107	-0.00147	-0.0319
	(0.0145)	(0.0170)	(0.0220)	(0.0289)
Constant	-0.701**	1.936***	-0.341	4.524***
	(0.301)	(0.476)	(0.565)	(0.858)
Province FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
a_i	130	130	130	130
Observations	374	375	377	376
R^2	0.341	0.616	0.832	0.495
Provinces	29	29	29	29

Note: Standard errors are clustered by province. *** p<0.01, ** p<0.05 and * p<0.10.

There are two important caveats. The surveys, which are the basis for our empirical analysis, do not differentiate between central air and window units. We have no way of knowing what share of the installed units are central air from currently available other sources. Further, China started adopting air conditioners much later than the United States. As we have learned from Biddle (2008), there were significant drops in the price of air conditioners, which appear to be ongoing (Rapson, 2011). Further, the efficiencies of air-conditioning units are also improving over time (Rapson, 2011), which makes operating these units less expensive per unit of cooling service.

Finally, we have to be careful about the direct comparison here. EIA's statistic is a binary indicator at the household level whereas the Chinese statistics count air-conditioning units, which makes this number potentially larger relative to the U.S. number by construction.
U.S. personal income in 1993 was $23,562. China's urban per capita income in 2009 was 17175 RMB per capita and rural net income was 5153 RMB. If we used an official exchange rate, this would be equivalent to $2,685 in urban areas and $805 in rural areas. If we used a purchasing power adjusted exchange rate, such as the one based on the Economist's "Big Mac Index," this would be an urban income of $4,770 and a rural income of $1,431. Either way, China's air-conditioner penetration is near U.S. levels in 1993 at somewhere between 8% (nominal exchange rate) and 13% [purchasing power parity (PPP) adjusted exchange rate] of the per capita income.

This suggests that adoption in China happens at a significantly lower level of income than in developed countries. This is very likely due to higher efficiencies and lower prices.

Bibliography

Aebischer, B., G. Henderson, M. Jakob, and G. Catenazzi. 2007. Impact of climate change on thermal comfort, heating and cooling energy demand in Europe. ECEEE Summer Study.

AHRI. 2011. Air-Conditioning, Heating, and Refrigeration Institute. Available: http://www.ahrinet.org/default.aspx.

Akpinar-Ferrand, E. and A. Singh. 2010. Modeling increased demand of energy for air conditioners and consequent CO_2 emissions to minimize health risks due to climate change in India. *Environmental Science and Policy* 13(8):702–712.

Biddle, J. 2008. Explaining the spread of residential air conditioning, 2955-1980. *Explorations in Economic History* 45:402–423.

CEC. 2011. Residential Appliance Saturation Survey. The California Energy Commission. Available: http://www.energy.ca.gov/appliances/rass/.

DGTE. 2003. Energy Efficiency and Certification of Central Air Conditioners. Final Report April 2003. Volume 1. Directorate General Transportation Energy of the Commission of the European Union.

Downing, T.E., N. Eyre, R. Greener, and D. Blackwell. 1996a. Full Fuel Cycle Study. Report to the International Energy Agency Greenhouse Gas and R&D Programme. Environmental Change Unit Oxford Mimeo.

Downing, T.E., N, Eyre, R. Greener, and D. Blackwell. 1996b. Projected Costs of Climate Change for Two Reference Scenarios and Fossil Fuel Cycles. Report to the European Commission ExternE Project. Environmental Change Unit Oxford Mimeo.

EIA. 2011a. Air Conditioning in Nearly 100 Million U.S. Homes. Energy Information Administration. Available: http://www.eia.gov/consumption/residential/reports/air_conditioning09.cfm?src = email.

EIA. 2011b. RECS Survey Data Tables. Energy Information Administration. Available: http://www.eia.gov/consumption/residential/data/2009/#undefined.

EIA. 2011c. U.S. and Regional Tables. Energy Information Administration. Available: http://www.eia.gov/emeu/reps/appli/all_tables.html.

Ekins, P. 1995. Rethinking the costs related to global warming: A survey of the issues. *Environmental and Resource Economics* 6:231–277.

Fridley, D., G. Rosenquist, J. Lin, L. Aixian, X. Dingguo, and C. Jianhong. 2001. Technical and Economic Analysis of Energy Efficiency of Chinese Room Air Conditioners. LBNL Working Paper 45550.

IPCC. 2000. *Special Report on Emissions Scenarios.* Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IPCC. 2007. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Core Writing Team, R.K. Pachauri, and A. Reisinger. (eds.).Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IPUMS. 2011. 1960 Census: Instructions to Respondents. Integrated Public Use Microdata Series. Available: http://usa.ipums.org/usa/voliii/items1960.shtml#h27.

Isaac, M. and D.P. van Vuuren. 2009. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy* 37:507–521.

Koizumi, S. 2007. Energy Efficiency of Air Conditioners in Developing Countries and the Role of CDM. International Energy Agency. Mimeo.

Letschert, V. and M. McNeil. 2009. Material World: Forecasting Household Appliance Ownership in a Growing Global Economy. LBNL Mimeo.

Letschert, V.E., M.A. McNeil, and N. Zhou. 2010. Residential Electricity Demand in China – Can Efficiency Reverse the Growth. LBNL Paper LBNL-2321E.

Matsuura, K. and C.J. Willmott. 2011. Terrestrial Air Temperature: 1900-2008 Gridded Monthly Time Series (Version 2.01). Available:http://climate.geog.udel.edu/~climate/html_pages/Global2_Ts_2009/Global_t_ts_2009.html.

McNeil, M. and V. Letschert. 2005. Forecasting Electricity Demand in Developing Countries: A Study of Household Income and Appliance Ownership. ECEEE Summer Study.

McNeil, M. and V. Letschert. 2008. Future Air Conditioning Energy Consumption in Developing Countries and What Can be Done about It: The Potential of Efficiency in the Residential Sector. LBNL Working Paper. Available: http://escholarship.org/uc/item/64f9r6wr.

McNeil, M. and V. Letschert. 2010. Modeling diffusion of electrical appliances in the residential sector. *Energy and Buildings* 42:783–790.

National Bureau of Statistics of China. 1996–2010. China Statistical Yearbooks. Beijing. China.

NSS. 2011. Socio Economic Survey. National Sample Survey Office. Available: http://mospi.nic.in/Mospi_New/site/inner.aspx?status = 3&menu_id = 54.

Rapson. D. 2011. Durable Goods and Long-Run Electricity Demand: A Case Study of Air Conditioner Purchase Behavior. Working Paper. UC Davis.

Sailor, D. and A. Pavlova. 2003. Air conditioning market saturation and long-term response of residential cooling energy demand to climate change. *Energy* 28(9):941–951.

Schmalensee, R., T.M. Stoker, and R.A. Judson. 1998. World carbon dioxide emissions: 1950–2050. *The Review of Economics and Statistics* 80(1):15–27.

SEI. 1993. Towards a Fossil Free Energy Future: The Next Energy Transition: A Technical Analysis for Greenpeace International. M. Lazarus(eds.).Stockholm Environment Institute, Boston, MA.

Tol, R.S.J. 2002. Estimates of the damage costs of climate change. *Environmental and Resource Economics* 21:47–73.

U.S. Census Bureau. 2011. American Housing Survey. Available: http://www.census.gov/housing/ahs/#jump2.

Wolfram, C., P. Gertler, and O. Shelef. 2011. Timing is Everything: Poverty Alleviation and the Demand for Energy-Using Assets. University of California Haas School Mimeo.

World Bank. 2011. Living Standards Measurement Study. The World Bank Group. Available: http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,contentMDK:21610833~pagePK:64168427~piPK:64168435~theSitePK:3358997,00.html.

Zhou, N., D. Fridley, M. McNeil, N. Zheng, V. Letschert, J. Ke, and Y. Saheb. 2011. Analysis of Potential Energy Saving and CO_2 Emission Reduction of Home Appliances and Commercial Equipments in China. LBNL Working Paper LBNL-4607E.