Available online at www.sciencedirect.com
ScienceDirect
Resources, Conservation and Recycling 51 (2007) 847–869
Resources Conservation & Recycling
www.elsevier.com/locate/resconrec

Modeling obsolete computer stock under regional data constraints: An Atlanta case study

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Received 30 June 2006; received in revised form 6 December 2006; accepted 10 January 2007
Available online 6 March 2007

Abstract

In this paper, we report on our efforts to develop a research framework that can be used to quantify waste flows for different geographical areas in the face of limited waste data availability. We demonstrate this framework in our case study of obsolete computers in the Atlanta metropolitan area. We develop computer obsolescence rates at the national metropolitan level, and couple this data with economic information at the census tract level to generate product inventory estimates (PIE) of the stock of obsolete computers from both business and household sectors in the Atlanta metropolitan area. We seek to improve the accuracy of waste flow estimates for specific geographic areas over those of previous studies, provide an easily replicable and cost effective methodology, highlight the ensuing spatial implications for collection and recycling systems using GIS, and demonstrate the potential economic benefits from diverting electronic wastes within a region. The modeling framework we have developed is intended to be applicable to other regions and to other medium range durable goods discarded by households, businesses, or obtained from buildings.

Keywords: Computer recycling; Product inventory estimates; Material flow analysis; Modeling; Sustainable regional development; Atlanta

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0921-3449/$ – see front matter
doi:10.1016/j.resconrec.2007.01.007

1. Introduction

Each day, an estimated 163,420 computers and televisions, weighing more than 3500 t, become obsolete (Silicon Valley Toxics Coalition, 2004). The 300 million computers that were obsolete in the US, as of 2004, generated 2 million tonnes of plastic, a half million tonnes of lead, about one million tonnes of cadmium, over 500 t of chromium, and 200 t of mercury (National Safety Council, 2002). As much as eighty percent of this hazardous waste has been shipped to developing countries such as China (the largest importer) and Nigeria (a recent importer) (Basel Action Network & Silicon Valley Toxics Coalition, 2002). Annually, another 12 million PCs are sent to US landfills (Lundquist and McRandle, 2004). If this e-waste is not disposed of properly, toxic substances may be released, generating the risk of water pollution and soil contamination and, thereby, exerting negative impacts on adjacent neighborhoods and upon future development (see Blum, 1976; Hite et al., 2001; Katz, 2002). Moreover, waste disposal into landfills precludes that land from serving other competing needs. With rising land values in most urban areas, landfilling disposal has become costly (in economic and sustainable terms) and socially undesirable.

The bulkiness and hazardous waste components associated with much of the electronic waste stream complicate disposal efforts. At the same time, this waste stream may produce additional economic value from disassembly or recycling. Material recycling, along with the possibility of whole product resale and reuse, has proved to be an industry that generates positive impacts on a region's economy, leading to increases in total sales, job opportunities, and income level. Thus, encouraging new manufacturing activity through e-waste diversion in distressed areas could prove to be a promising economic development strategy that promotes urban sustainability (see Goldman and Ogishi, 2001; Wisconsin Department of Natural Resources, 2002; Massachusetts Department of Environmental Protection, 2000).

Acknowledging the potential benefits from diverting e-wastes from landfills, the US government has mandated regulations in the Federal Resource Conservation and Recovery Act (RCRA) to manage this enormous waste stream. Below the federal level, many states have created more stringent regulations to address hazardous waste from discarded electronics. By November 2005, six states in the US had enacted a ban on landfilling CRTs (California, Maine, Massachusetts, Minnesota, North Carolina, and Virginia). Further, at least eight additional states were planning or considering adopting a ban.[1] Following on recent state level initiatives, the federal Electronic Waste Recycling Promotion and Consumer Protection Act (EWRPCPA) was introduced in 2005. The act, if passed, would ban e-waste generated by households and businesses from landfills, and only allow disposal of e-waste through recycling (The Library of Congress, 2005).

For enforcing e-waste regulations and designing efficient recycling system, policy makers require tools to assess the potential impacts of recycling programs on the environment, economy, and community. However, the most fundamental information required to conduct such studies, such as product lifespan, generation volume, spatial distribution, and discard rates, is not systematically or regularly collected at the regional level. One approach, large-scale surveys, is likely to be too costly and time consuming to produce waste flow data for

[1] Information was compiled from multiple sources, mainly including: Northwest Product Stewardship Council, US EPA, National Caucus of Environmental Legislators, and Competitive Enterprise Institute.

each product of concern. Thus, there is a pressing need to develop a valid methodology for enhancing the accuracy of product waste flow estimation at the local level.

In response to such data needs, researchers have investigated various methods for examining e-waste material flows to improve the accuracy of estimation models, and studies in this area have been especially fruitful in the last decade (see Berger, 1997; Darby and Obara, 2005; Leigh and Realff, 2003; Linton et al., 2002, 2005; Marx-Gomez and Rautenstrauch, 1999; McLaren et al., 1999; Owens et al., 2000; Tucker, 1997; Tucker et al., 1998a,b). However, previous product flow analysis tends to focus on temporal analysis and ignore the pertinent spatial components. These analyses appear to presume (erroneously) that information about product sales or ownership rate is available at any geographical level.

We report here on our efforts to develop a research framework that can be used to quantify waste flows for different geographical areas in the face of limited waste data availability. We demonstrate this framework in our case study of obsolete computers in the Atlanta metropolitan area (referred to as "Atlanta" hereafter). We first develop computer obsolescence rates at the national metropolitan level from published computer usage surveys. Then we couple this data with economic information at the census tract level to generate product inventory estimates (PIE) of the stock of obsolete computers from both business and household sectors in Atlanta. Like most US metro areas, Atlanta is coping with issues of sprawl, inner-city redevelopment, and sustainability issues in general. Thus, we expect our research results will be generalizable and transferable to other regions.

We begin with the acknowledgment that used computers may not be disposed of immediately when they become obsolete. Thus, we differentiate obsolete and discarded computers in the end-of-life analysis by dividing our study into a three-step sequential analysis: computer inventory analysis, obsolete computer estimation, and discarded computer estimation. Our goal is to improve the accuracy of waste flow estimates for specific geographic areas over those of previous studies, as well as to provide an easily replicable and cost effective methodology. We also seek to highlight the ensuing spatial implications for collection and recycling systems using Geographic Information Systems (GIS). In the absence of an Atlanta regional input–output model with the necessary industry specificity, we employ a classical production function to estimate job creation by incorporating the characteristics of the recycling industry. Our results indicate there are potential economic benefits from diverting electronic wastes within a region. The modeling framework discussed here is intended to be applicable to other regions and to other medium range durable goods discarded by households, businesses, or, obtained from buildings.

2. Literature review of product flow analysis

Our analysis of previous research on product flows reveals two general approaches. One approach focuses on tracing the beginning of the product life cycle; that is, it estimates the number of obsolete products based on product sales or ownership information. This approach tracks the waste stream by the unit of product (for example, number of computer monitors). The second approach tracks the chemical substances at the end of the product life cycle, such as the substances decomposed from waste disposed of in landfills (see Christensen et al., 2001; Isidori et al., 2003; Kjeldsen et al., 2002; Mersiowsky, 2002). Because the second approach is still underdeveloped and involves greater variances, we will adopt the first approach as elaborated below. We first review studies on product flow in general, then focus on studies of computers, the product of our case study.

2.1. Review of product flow analysis in general

The most straightforward method for estimating waste generation is the step-down approach, where the waste generated in a specific geographical area is derived as a percentage from a larger area for which statistics are available. In the case of the US, it is frequently possible to find some national estimates of consumption or generation for most products. Then a state or locality makes the (crude) assumption that its share of the national population would translate into its share of the national product (see Massachusetts Department of Environmental Protection, 1998).

In previous studies, waste generation estimation typically involves three steps: product stock estimation, obsolete rate estimation, and disposal/recycling rate estimation. Because products vary greatly in terms of their turnover rate and user behavior in disposing of them, researchers generally focus on one product at a time seeking to fully incorporate its characteristics.

In the case of photocopiers, Marx-Gomez and Rautenstrauch (1999) employed a four-stage model focusing on the introduction, growth, maturity, and decrease of a specific product. To increase the likelihood of data availability, they innovatively divided the product failure process into three sub-processes – early failure, failure by accident, and failure by wear and tear – so that some information could be obtained from market surveys. They further assumed the failure process to be of a bathtub form (see, for example, Pulcini, 2001), which depicts the distribution of product failure over the product life span. The intercept of the curve shows the failure rate for products that fail within 1 year of use. The curve then flattens out because the product experiences a low failure rate if there is no failure after 1 year of use. Over subsequent years, the depreciation of the product may increase, with its rate dependent on a variety of factors, such as frequency of use, product design, and parts design and manufacture process.

The model of small electronic equipment, such as mobile phones, still follows the general product cycle, but has been adjusted to take into account the small size and fashion requirements (McLaren et al., 1999). This model incorporates a ‘bottom drawer’ or ‘hibernation stocks’ effect that reflects the tendency of consumers to stock the outdated products for a relatively long period instead of discarding immediately after replacement.

Linton et al. (2002, 2005) proposed three scenarios to estimate future waste inventory in the case of TV CRTs: (1) a base scenario when there is no technological change and television sales remain constant for the next half century, (2) a moderate rate of displacement, following the historical rate of replacement of black-and-white by color televisions; and (3) a rapid phase-out of CRT technology, following the rate predicted by the Electronics Industry Association (EIA). While Linton et al. assumed the TV set failure process also follows a bathtub curve, they capture the number of TV sets entering the waste stream as the units failed in a certain year m, plus all those failed in previous years but only disposed of in year m.

Tucker (1997) and Tucker et al. (1998a,b) case studies are of non-electronic products (paper recycling), but their model is of relevance to other durable goods analysis in that it incorporates spatial and temporal variability of different households. Tucker et al. focussed on the household participation rate in recycling over a much shorter temporal period than that of other models. The modeling focus is important to our research discussed below which employs the spatial location of households and their demographic characteristics in modeling the inventory of obsolete computers for a metropolitan area.

Although the models discussed are specific to a unique type of electronic product, they share a common approach typically used for durable goods. That is, each differentiates a product's obsolescence, failure, and disposal rate. In doing so, they increase the accuracy of temporal analysis of these products. Spatial analyses of e-waste generation are underdeveloped. Further, a well-designed research model may not be feasible due to the lack of data at a specific geographical scale.

2.2. Review of product flow analysis of computers in particular

Computers are one of the most rapidly evolving of all products and have the potential to generate large volumes of obsolete units every year. Thus, they have become a primary focus of researchers interested in estimating waste flows. At present, there are no official statistics readily available for the computer inventory in the US. Neither are there any for the computers that have become obsolete. Since 1984, the US Census Bureau has collected data on household computer ownership as a supplement to the basic Current Population Survey (CPS). Some private companies (for example, Mindbranch, Nielsen Media Research, Park Associates, and TechnoMetrica Market Intelligence) conduct small-scale surveys of product penetration rates at the regional or state level. To determine the total product stock at a user-specified geographical scale, however, still requires modeling.

Earlier studies estimated that by 2005, a total of 680 million PC's would have been sold worldwide, and that 315 million computers became obsolete between 1997 and 2004 (US EPA, 2003). The accuracy of these estimates is dependent upon the accuracy of the computer obsolescence rates that were used. Researchers generally believe that the lifespan of personal computers has decreased from 4 or 5 years to approximately 2 years (see Smith, 2001; Leigh and Realff, 2003). This trend may have reversed, as the recession lowered business spending and the early euphoria surrounding information technology and productivity faded (Wall Street Journal, 2003). Instead of assuming a uniform life span, a research study from North Carolina using a 10-year discard rate, assumes: no computers discarded in the first 2 years after purchase; 5% discarded in the third year; 10% discarded in years four and five, and 15% discarded between years 6 and 10 (North Carolina Department of Environment and Natural Resources, 1998). After computers are no longer used by their original owners, it has been estimated that about 75% remain in storage because their owners perceive them to be valuable, 15% are landfilled, and only about 10% are recycled (Goodrich, 1999).

The first systematic, and most frequently quoted research on obsolete computer estimation, was conducted by Carnegie Mellon University (CMU) in 1991. The results of this study are highly dependent on several key assumptions on the increasing rate of computer ownership rate, replacement rate, recycling/reuse/storage rate, and lifetime of computers. Dramatic changes in these attributes of computer usage explain why the same investigator's

1997 study arrived at significantly different results. On a global basis, CMU's 1991 study estimated that about 148 million personal computers would be landfilled and 2 million would be recycled by 2005. Then the 1997 study predicts that by 2005 only 55 million PCs would be landfilled and 143 million PCs recycled (Matthews et al., 1997).

There are two other major studies of computer stock estimation. The "Electronic Product Recovery and Recycling Baseline Report," completed by National Safety Council (1999), provides estimates at the national level through survey analysis. The other study conducted by the Massachusetts Department of Environmental Protection, 1998) makes significant assumptions such as: the life cycle of a CRT – including use and storage – is 10 years; there is a constant flow of CRT items; and workplaces have approximately the same number of CRTs as residences.

More recent studies have suggested a correlation of demographic characteristics with household recycling behavior (see Berger, 1997; Owens et al., 2000; Darby and Obara, 2005; Leigh and Realff, 2003). Accordingly, Leigh and Realff (2003) developed a regional material flow model with a case study in computer recycling in Atlanta region. In their model, the material flow analysis is divided into three sub-sections: input flow (product sales), output flow (disposal and recycling), and accumulation (the difference between input and output flow, or "stock"). Their model also considers the interregional material flow accompanying population migration, which makes it more robust. By linking demographic information to computer ownership estimates, the model of Leigh and Realff (2003) provided a durable product disposal framework for analysis that can be broken down into the smallest scale for which demographic information is available. Their study, however, was limited to the estimation of residential electronics, which could be only a portion of the total computer stock.

3. Refinement of computer inventory analysis: Atlanta case study

The prior work published in (Leigh and Realff, 2003) demonstrates that national data can be combined with local population data to give estimates of residential computer ownership by household income level. Using the same approach, we refined the geographical scale of the model to achieve improved accuracy and increased scope by including business computers as well. We coupled population data from the Atlanta Regional Commission (ARC) with computer use data from the Current Population Survey (CPS), to create a more robust model of the metropolitan area's computer stock that includes estimates of multiple computer ownership for households. Our recent research is also expanded to incorporate business computer waste estimates by linking industry employment data with computer use rates. We assume that the pattern of computer usage in the Atlanta metropolitan area parallels that of national metropolitan data on average. We then extrapolate the national data to Atlanta to estimate computer stock at the census tract level (totaling 589 census tracts in the Atlanta 13-county region), for which household income and employment data is available.[2] This allows us to present a much finer geographical scale of analysis than found

[2] Because less than 300 households in the aggregated Georgia metro area were included in the CPS 2001 Computer Use Survey, we consider the sample size too small to represent the 1,356,592 households in the 13-county region of Atlanta Regional Commission (ARC).

Table 1
Household computer ownership rate at national metro level in 2001

Family income, $ (in 1999)	Households by computer ownership (%)			
	Own three or more	Own two computers	Own one computer	Do not have
0–19,999	1	4	26	69
20,000–34,999	2	7	42	49
35,000–49,999	4	11	54	31
50,000–74,999	7	17	58	19
75,000 or more	15	26	51	9

Source: Rate was calculated based on CPS September 2001 Computer and Internet Use Supplement Survey (US Census, 2001b).

in previous studies. We elaborate on our calculation methods of residential and business computer stock estimates respectively below, followed by our spatial presentation of our results using Geographic Information Systems.

3.1. Household computer stock estimate

Due to the increasing rate of technology advances and product upgrades, the household computer ownership rate in the US has risen dramatically, with many households now owning more than one computer. In October 1997, the US Current Population Survey (CPS) began to collect data on multiple computer ownership (2, 3 or more), in addition to the binary question in previous surveys asking whether a household does or does not have a computer. Accordingly, using 2001 data, we develop estimates for four categories of computers per household (see Table 1). Following the approach of Leigh and Realff (2003), we link computer ownership with household income levels for surveyed households in metropolitan areas nationwide. Our summarized household computer ownership rate is shown in Table 1.

Based the computer ownership rate in Table 1, we calculate the total computer ownership in Atlanta using Eq. (1) below:

$$C_{\mathrm{H}} = \sum_{i=1}^{3}\sum_{j=1}^{5} i \times \mathrm{OwnershipRate}_{ij} \times \mathrm{HH}_j \qquad (1)$$

where C_{H} is the total number of household computers, i the number of computers in the household, namely, when $i = 1$, the household has one, computer; $i = 2$, two computers; $i = 3$, the household has three or more computers, $\mathrm{OwnershipRate}_{ij}$ the % household of income category j that have i number of computer(s) at home, HH_j the numbers of households by each household income category j, and j is the household income category: $j = 1$, household income below \$19,999; $j = 2$, household income between \$20,000 and \$34,999; $j = 3$, household income between \$35,000 and \$49,999; $j = 4$, household income between \$50,000 and \$74,999; $j = 5$, household income above \$75,000.

Following the steps shown in Fig. 1, for the 13-county Atlanta region, we estimate that 37% of Atlantans had a computer at home in 2001, and that Atlanta's household computer

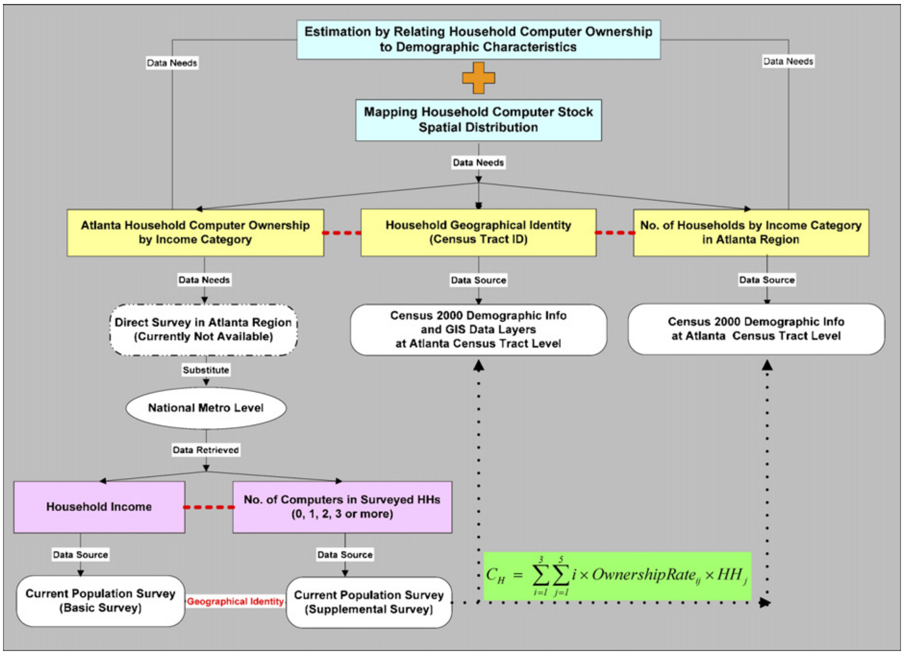

Fig. 1. Illustration of household computer stock estimation method.

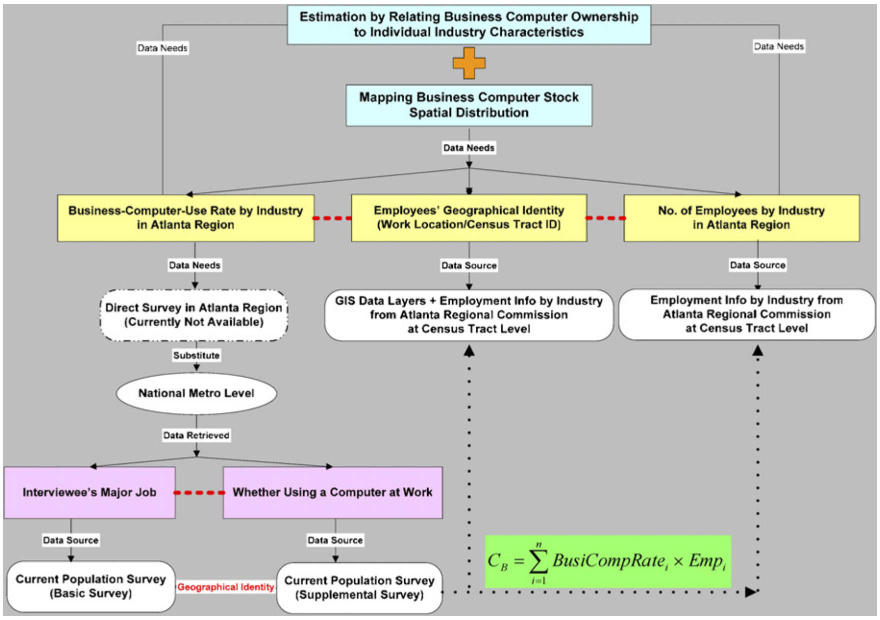

Fig. 2. Illustration of business computer stock estimation method.

stock would have been 1,362,424 in 2001. While some households have no computers and others have multiple ones, our estimated number of computers exceeds the number of households (1,356,592) of the entire region.

To account for sampling and non-sampling errors, we further apply the CPS-given formula to calculate the confidence interval of the computer use rate. Our results indicate that with 90% probability, the household computer stock is estimated to be between 1,318,935 and 1,409,215 (see Appendix B for details). However, it is possible that the upper bound of the estimate may still underestimate the real stock because the CPS survey does not allow for households having *more than three* computers. In addition, the CPS Survey instructs respondents, *"if necessary—Do not include old computers that are in the household but are not used"*[3]. This may exclude a significant number of computers that are ready for recycling, which is the information we eventually want to capture.

3.2. Business computer stock estimate

In addition to household computer ownership information, the 2001 CPS Supplemental Survey asks interviewees whether a computer is used at their primary workplaces. By integrating the "supplement" and "basic" surveys using geographical identifiers, we are able to identify the primary job of each interviewee and, subsequently, calculate the computer use rate by industry. Matching the rate with Atlanta's employment data at the census tract level provided by the Atlanta Regional Commission (ARC), we can estimate the business computer stock for the Atlanta region using Eq. (2) below. The complete calculation process is illustrated in Fig. 2:

$$C_\mathrm{B} = \sum_{i=1}^{\mathrm{n}} \mathrm{BusiCompRate}_i \times \mathrm{Emp}_i \tag{2}$$

where C_B is the total number of business computers; $\mathrm{BusiCompRate}_i$ the % of employees that use computers at work in industry i, and Emp_i is the no. of employees in industry i of each census track.

It is through industry classification codes that we can connect the CPS and ARC data, but the CPS Survey employs a more detailed industrial classification system than ARC. Further, to calculate the confidence interval of the computer use rate suggested by the CPS, we need to know the total number of employees by industry in the entire metropolitan area. This data can only be obtained from *County Business Patterns* (CBP), which uses an industrial classification system that is different from the CPS and ARC. To overcome this problem, we weight the industry subcategories in CPS by the number of employees to match the industry with the ARC's classification categories, and identify the crosswalk for all three classification systems used by ARC, CBP, and CPS, as shown in Appendix Table A1.[4]

[3] *Source*: CPS Computer and Internet Use Supplement Technical File Section 9-1at http://www.census.gov/apsd/techdoc/cps/cpssep01.pdf.

[4] Another challenge we identified when integrating the data is that the County Business Patterns do not include employees in nonemployer business or public administration. We assume that computers used by nonemployers are already included in household computer stock estimate, thus we only focus on capturing the jobs in public

Table 2
Computer use at work by industry at national metro level, 2001

Industry classification by ARC	Computer use by industry (%)
Construction	27.37
Manufacturing (i)	55.47
Transportation, communications, and utilities (ii)	54.27
Retail trade	39.63
Wholesale	61.39
Finance, insurance, and real estate	81.51
Service industry (iii)	63.48
Public administration	77.33

Source: Calculated by the author using CPS 2001 raw data. *Note*: The value of (i) shows the weighted percentage of manufacturing of durable goods and non-durable goods; (ii) weighted percentage of transportation, communication, and utilities; (iii) weighted percentage of eight categories: (1) business, auto and repair services, (2) personal services, excl. private households, (3) entertainment and recreation services, (4) hospitals, (5) medical services, excl. hospitals, (6) educational services, (7) social services, and (8) other professional services.

Ultimately, we derived the computer use rate of eight industries at the national metropolitan level shown in Table 2. Our sensitivity analysis for business computers yielded an estimate of computer stock in the Atlanta region between 1,389,953 and 1,409,879 in 2001[5] (the details are shown in Appendix Tables B3 and B4). This result is consistent with the assumption in the Massachusetts' study that workplaces have approximately the same number of CRTs as residences.

3.3. Spatial analysis

Using the tool of Geographic Information Systems (GIS), we mapped the spatial distribution of household and business computers in Atlanta in 2001. As shown in Fig. 3, both business and household computers cluster around urban centers, and business computers highly concentrate along interstate roads. The two census tracts with the largest volume of household computers in Atlanta also have the largest percentage of households in the highest income levels recorded by the US Census: Alpharetta in the north Fulton County and Brooks and Peachtree City in the south Fayette County. This reflects our modeling assumption that computer use rate is correlated with demographic characteristics, in this case, household income. Generally speaking, household computers are more widely dispersed than business computers, which may complicate the process of used computer collection and make it more challenging than handling business computers.

administration. We calculate the percentage of public administration jobs among total employment for all MSAs in 2000 Census Summary File 3, and estimate the employers in public administration at the national metro level as the product of this percentage and the total employment in national metro, which is available through Census.

[5] We notice from ARC regional data that the region also has employment recorded as proprietors and miscellaneous, which is 14% of the total regional employment. This proportion of employment is not included in the eight categories of ARC employment classification at the census tract level. We assume that the percentage of employment as proprietors and miscellaneous in each census tract is the same; that is 16% of the total of the eight-category groups shown in ARC data. Then we estimate the number of employees categorized as "proprietors and miscellaneous" in each census tract on the basis of ARC eight-category employment data. Subsequently, we adopt the computer use rate for service industry to estimate the computer use for these employees.

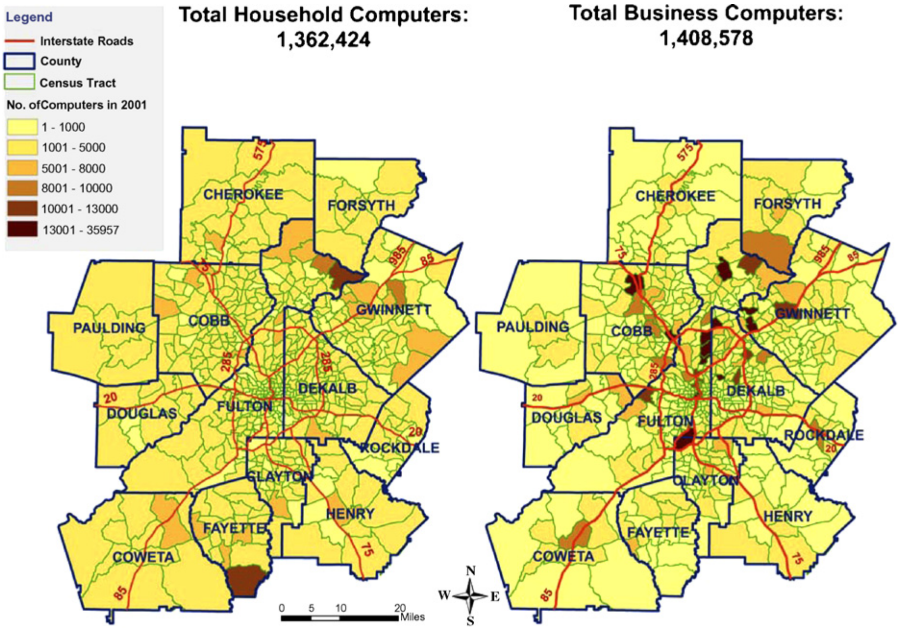

Fig. 3. Computer distribution in Atlanta metro in 2001.

4. Product flow analysis of obsolete computers

Although the CPS includes information about computer use in residences and at the workplace, it does not provide any information about individuals' use of computers over time. Thus, we do not have any data on the actual life span of computers, or, in what ways obsolete computers are disposed. Consequently, we create estimates through a two-step analysis. In this section, we only discuss the total number of computers that may become obsolete. When we evaluate the economic impact of recycling computers in the next section, we expand our consideration of the discarded computers by employing different discard rates along the computer life span.

4.1. Analysis of obsolete computers from households

Due to a lack of supporting information on household usage of computers, we have relied on the household computer age profile information (Fig. 4) derived from Leigh and Realff's model of year 2000.[6] Assuming such a distribution remains the same in 2001 (our study year), we calculated the age profiles of household computer ownership in Atlanta for 2001 (results are shown in Appendix C). We further assumed two scenarios of the life span of home computers, 3 or 5 years, and estimated the household computer ownership. Our results

[6] Because of data constraints, Leigh and Realff made two important assumptions: (1) the year of CPS survey is identical to the year of computer purchase, and (2) all obsolete computers remain in the households that purchased the equipment as of 2000. This could have resulted in an underestimation of old computers.

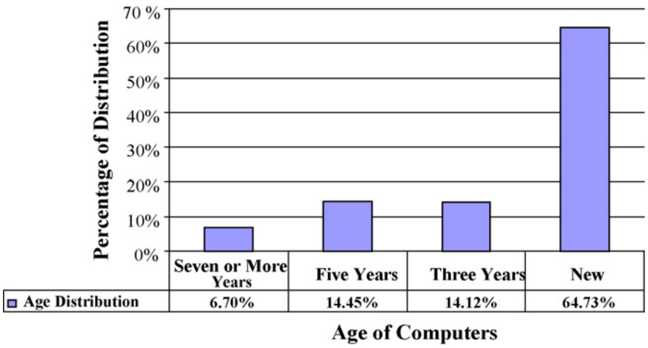

Fig. 4. Household computer age distribution in Atlanta metro in 2000.

are presented in Table 3. This part of the analysis yields the number of computers that need to be disposed of properly, or, the maximum stock that can be recycled in Atlanta. Readily apparent is the fact that the lifespan of computers greatly affects the results of analysis. In total, our conservative estimate indicates that at least 278,882 computers purchased by the year 2001 would have become obsolete in Atlanta. In contrast, our upper estimate indicates that nearly 1.5 million computers were obsolete.

4.2. Analysis of obsolete business computers

Because business operations are less likely than households to store computers, we assume that both the turnover and discard rates of business computers are higher. In the absence of detailed profiles of computer ownership by business sectors, we calculated three scenarios of obsolescence: (1) 15%, (2) 30%, or (3) 40% of the business computer stock of 2001 are older than 5 years. Based on the business computer rates at the national metropolitan level (Table 2), we estimate the number of obsolete computers at workplaces would range from 205,504 to 563,952 in 2002, as shown in Table 4.Combining the household and business sector estimate, we estimate that 484,386 (=278,882 + 205,504) to 1,060,964 (=497,012 + 563,952) computers would have become obsolete in Atlanta by

Table 3
Estimated number of obsolete households computers in Atlanta in years 2002 and 2004

Scenarios of HH	No. of obsolete HH computers		
Computer life span	Base estimate	Lower estimate	Upper estimate
Year of 2002			
3-year	480,509	465,171	497,012
5-year	288,077	278,882	297,971
Year of 2004			
3-year	1,362,424	1,318,935	1,409,216
5-year	480,509	465,171	497,012

Note: The estimation is limited to the computers purchased before 2001.

Table 4
Estimated number of business computers to be obsolete in Atlanta in 2002

Scenarios obsolescence of rate (%)	No. of business computers to be obsolete		
	Base estimate	Lower estimate	Upper estimate
15	208,493	205,504	211,482
30	416,986	411,008	422,964
40	555,981	548,011	563,952

2002. With our assumption that each computer weighs 50 pounds (about 23 kg), there would be 12,110–26,524 t of obsolete computers in 2002. This is the estimated computer stock that could have been diverted from landfills by recycling, reuse, or remanufacturing in Atlanta in 2002.

5. Economic impact analysis of used computers in Atlanta

Extending the life cycle of computers that would otherwise be landfilled can generate local jobs and revenues, and our analysis of obsolete computer stock allows us to estimate such impacts[7]. We employ a classical economic production function taking into account the industry's characteristics of scale economies and potential declining labor rates. This established relationship enables us to roughly quantify the potential job creation based on the volume of obsolete computers. Although this approach does not estimate revenue impact directly, it requires much less data compared to other complex regional economic impact models, such as input–output modeling or social accounting matrix modeling. The production function can be expressed as in Eq. (3) or (4):

$$Y = AL^{\mathrm{a}}K^{\mathrm{b}}T^{\mathrm{c}} \tag{3}$$

Or, in logarithmic form:

$$\ln Y = \ln A + a \ln L + b \ln K + c \ln T \tag{4}$$

where Y is the production output, A the A scalar, a, b, c the fractional components that add up to 1, L the measure of the flow of labor input, K the measure of the flow of capital input, and T can be a measure of land, energy, technology, and other production requirements.

Assuming that most capital investment (K) is required at the start-up of the recycling business and that other production requirements (T) of used computer recovery vary little from region to region, we regard labor (L) as the major and single input that varies in response to the tons of computers processed. In other words, we expect a production function in particular to the industry of used computer recovery as in Eq. (5):

$$\ln(\text{tonnes of computers processed}) = \alpha + \beta \ln(\text{jobs needed}) \tag{5}$$

[7] While we acknowledge that more recycling activities will reduce the job opportunities in landfills, Georgia's 2005 Waste Characterization Study indicates that about 0.1% of computers are landfilled (R.W. Beck Inc., 2005). Thus, we believe that job losses in the landfill industry would be insignificant.

Or

$$\ln(\text{jobs needed}) = \alpha + \beta \ln(\text{tonnes per year processed}) \tag{6}$$

In terms of data inputs, our structuring of an ordinary least squares (OLS) regression is confounded by the absence of employment data for computer recycling. The industry of recovering used computers has not been as well defined in economic data collection as has that for traditional industries, such as agriculture or construction. Theoretically we can differentiate various options of product recovery, such as recycle, reuse, remanufacture, resale, and de-manufacture. In practice, several of these processes are integrated as a chain in business operations, but different establishments may choose to engage in different combinations of these processes. Moreover, some establishments conduct both recycling and non-recycling business, but the division between the two activities is unknown.

All of these complications exist within the official industry classification system, North American Industry Classification System or NAICS, in which data on firms is only presented in aggregate form by industry sector. Further, NAICS does not distinguish recycling activity within each industry sector. The most relevant industry codes we can identify in NAICS are: (1) 423,430 computer and computer peripheral equipment and software merchant wholesalers, (2) 423,930 recyclable material merchant wholesalers, and (3) 811,212 computer and office machine repair and maintenance. Given the data constraints, we define "computer recycling" in our analysis as a general term, which involves one or more of the activities and services that extend the life cycle of computers.[8]

Further, because NAICS does not explicitly delineate industries engaged in computer recycling from other electronics products, we turned to the *Economic Census Industry Series* of national establishments to calculate the percentage of establishments specifically engaged in computer recycling business. Assuming a positive linear relationship between the number of establishments and number of employees, we then multiply the rate by the number of the Atlanta employees aggregated by NAICS codes to obtain an estimate of the number of computer recycling jobs in Atlanta in 2002 (see Table 5). In total, we estimate that there were 2238 employees in the computer recycling industry in Atlanta in 2002.[9] Following the same approach, we calculated the employment for the regions for which computer data is available (see Table 6).

We then inputted the data in Table 6 to run the OLS regression and arrived at the results in Eq. (7). The resulting R^2 of 0.779 suggests a relatively satisfactory goodness-of-fit, and the independent variable (the natural logarithm of the volume of the computers processed) is statistically significant at 0.05 level ($t = 2.319$). The standard errors are provided in parenthesis:

$$\ln(\text{jobs needed}) = \underset{(1.129)}{2.617} + 0.570 \underset{(0.175)}{\ln(\text{tonnes per year processed})} \tag{7}$$

[8] This is more comprehensive than estimating the employment by examining the list compiled by Georgia Department of Natural Resources, which includes about 30 establishments (including both companies and non-profit organizations) that were undertaking electronics recycling business as of 2004.

Table 5
Estimated employment engaged in computer recycling industry in Atlanta MSA in 2001

Corresponding NAICS industry sector[a]	NAICS definition	Establishments specific to computer industry based on NAICS definition (%)	No. of employees in Atlanta MSA in 2002[b]	Adjusted No. of employees in Atlanta MSA in 2002[c]
423,430 computer and computer peripheral equipment and software merchant wholesalers	Establishments primarily engaged in the merchant wholesale distribution of computers, computer peripheral equipment, loaded computerboards, and/or computer software	12[d]	10,000–24,999	2100
423,930 recyclable material merchant wholesalers	Establishments primarily engaged in the merchant wholesale distribution of automotive scrap, industrial scrap, and other recyclable materials. Included in this industry are auto wreckers primarily engaged in dismantling motor vehicles for the purpose of wholesaling scrap	1[e]	1,000–2,499	18
811,212 computer and office machine repair and maintenance	Establishments primarily engaged in repairing and maintaining computers and office machines without retailing new computers and office machines, such as photocopying machines; and computer terminals, storage devices, printers; and CD-ROM drives	8[f]	1,494	120
Total				2238

[a] These are 2002 NAICS codes which have some differences from those of 1997.

[b] Data source: US Census. County Business Patterns (CBP) data on employment in Georgia counties. 2001a. Note that the CBP data is based on NAICS codes and may not exactly match the businesses handling computers in particular.

[c] This column shows the results of our adjustment based on CBP data in column (3) and national survey results in column (4).

[d] Calculations are based on data from 2002 Economic Census Wholesale Trade Industry Series (US Census, 2004). Out of 13,732 establishments for Computer and Computer Peripheral Equipment and Software Merchant Wholesalers at the national level, 1646 establishments operate business for used computer equipment, and 11 establishments operate nonferrous metal scrap. This suggests that 12% of establishments in this category operated business specific to used computers at the national level in 2001.

[e] The definition of this sector suggests that a dominant amount of materials recycled in this category is from autos. Without any other data support, we assumed that the generation of auto scrap was much larger than that of computer e-scrap given the large difference in volume of each single unit. Thus, we assumed that only 1% of the employment in this industry is involved with recyclable materials from computers.

[f] Calculations are based on data from 2002 Economic Census Other Services (except public administration) Industry Series. Out of 5876 establishments for computer and office machine repair and maintenance at the national level, 4680 establishments operate computer and data processing equipment repair and maintenance, which makes up 80% of total establishments in this category. When excluding repair and maintenance for data processing equipment and for regular product tearing-out, we assume that 10% of these 4680 establishments would operate computer repair and maintenance business specifically for computer refurbishment and recycle. That is to say, about 8% of the establishments in this sector may fit into the computer recycling industry.

Table 6
Computer recycling in selected states

Region	Computers processed (tonnes/year)	No. of computer recycling employees
San Mateo county, California	600	302
Massachusetts state	5514	2559
New hampshire state	74	339
Rhode Island state	97	114
Washington state	1414	839

Note: Employment data is estimated by the authors. Computer data is compiled from multiple sources, including: San Mateo County Recycleworks in CA: http://www.recycleworks.org/ewaste/. Undated. Massachusetts: Northeast Recycling Council Inc. (NERC). Recycling and the environment: facts about recycling in Massachusetts. 2003 www.nerc.org/fsheets/ma-factsht1 1-03.html. As of year 2001. New Hampshire: Northeast Recycling Council Inc. (NERC). Recycling and the environment: facts about recycling in New Hampshire. 2003 www.nerc.org/fsheets/nh-factsht11-03.html. As of year 2002. Rhode Island: Northeast Recycling Council Inc. (NERC). Recycling and the environment: facts about recycling in Rhode Island. 2003 www.nerc.org/fsheets/ri-factsht1-03.html. As of year 2002. Washington State: Washington State Department of Ecology, Solid Waste and Financial Assistance Program (2004). Implementing and Financing an Electronic Product Collection, Recycling, and Reuse Program in Washington State. Interim Report to the Legislature (ESHB 2488). As of year 2002.

Following this derived relationship, if all the obsolete computers as we estimated in Section 4 are processed, we estimate that 2922–4570 jobs would be created. This would be an increase ranging from 30% to more than 100% of the current level of jobs (2238 jobs as we estimated above). If 50% of the stock is processed, then 1968–3078 jobs would be created. That the lower bound of our estimate is below our employment in 2001 could be a by-product of our conservative analysis in both computer stock and employment estimates. Moreover, our analysis is an underestimate of the employment that would be created from greater computer recycling, because the computer collection method is still unknown (i.e. drop-off, or collected through Municipal Solid Waste system, or collected through 1-day event). Thus, our estimates cannot capture employment creation for recycling collection and processing activities that is considered quite labor intensive.

6. Summary and policy implications

By relating the computer rate at the national metropolitan level to economic information at the census tract level, we estimated the total computer stock for the Atlanta metropolitan area. Our results are consistent with the assumption in previous studies (e.g., MA DEP, 1998) that workplaces have approximately the same number of CRTs as residences. In total, we estimate that there were nearly three million computers in Atlanta in 2001. On average, 37% of Atlantans had a computer at home, and 60% of Atlanta workers used a computer at work in 2001.

In the case of our household computer analysis, we were able to estimate the number of obsolete computers in two scenarios of product life span. The wide range of results derived from our analysis suggests that additional product lifespan information (for sectors and regions) is critical for improving life-cycle analysis. Because there are no official data on business computer use, we designed three arbitrary scenarios of business-computer obsolescence rates: (1) 15%, (2) 30%, and (3) 40% of the business computer stock in 2001 that was five or more years old and ready to be replaced. From this, we estimated that 205,504–563,952 business computers would have been obsolete in Atlanta in 2002. Aggregating household and business computer stock, we conclude that between 484,386 (=278,882+205,504) and 1,060,964 (=497,012+563,952) computers would have been obsolete in Atlanta in 2002. If all these computers were processed for recycling, we conservatively estimate that 2922–4570 jobs would be created, representing an increase that ranges from 30% to more than 100% of the current level of jobs. Because we selected to use the conservative scenario for each step of our analyses, the upper estimate of our results may still tend to be an underestimate of the positive economic impacts. In addition, because we limited our analysis to the individual sector level, the economic benefits from inter-sector activity, presumably a significant portion of the total benefits, are not captured here.

Our conservative results demonstrate significant economic benefits could be realized if obsolete computers are diverted from landfills and storage, idled capital is transformed into new revenue, and new employment is created within the regional economy. Our finding suggests that recycling may promote the region's development in economic terms and by preserving environmental quality through reductions in air pollutants emission, groundwater contamination, and raw material consumption. This points to the efficacy of public policy support for banning e-waste from landfills and encouraging the public to recycle their computers at the end of the product life cycle. In practice, the modeling efforts we presented here may enhance researchers' ability to quantify environmental benefits more accurately and at a more refined geographic level. Efforts to do so are the focus of our future research.

Based on our research, we find the accuracy of waste estimation appears more constrained by data availability than by methodology. Thus, effective waste management and diversion requires new efforts of data collection, monitoring and sharing. Though for-profit recyclers typically keep data confidential for competitive considerations, the public sector could create incentives for private sectors to share their data thereby increasing data transparency in product and material flows. Additionally, the US Department of Commerce should consider revising the North American Industry Classification System to separate the industry sector of used material processing. Research on recycling industries, changing trends in closed loop production, and progress towards sustainability will continue to be hampered until such a revision is made.

While the research presented here was limited to one product and one metropolitan region, the primary goal of our quantitative analyses was to illustrate the development of a research framework for obsolete product stock under regional data constraints, rather than to create accurate information for investment decisions. Future analyses are needed to test whether our research method can be extended to other types of durable goods that follow the same product-use pattern as computers, such as cell phones, printers, and carpets.

Acknowledgement

The research team acknowledges the support by NSF DMI Materials Use: Science, Engineering, and Society (MUSES) Program, Award No. 0424664.

Appendix A. Crosswalk of industrial classification

See Table A1.

Table A1
Industry classification comparison of ARC, CPS, and CBP

ARC classification	Current population survey classification	County business pattern classification
Construction	3 construction	23 construction
Retail trade	10 retail trade	44 retail trade
Wholesale trade	9 wholesale trade	42 wholesale trade
Manufacturing	4 manufacturing—durable goods	
	5 manufacturing—non-durable goods	
	Total 4 + 5	31 manufacturing
Transportation, communication, utilities	6 transportation	38 transportation and warehousing
	7 communications	51 information
	8 utilities and sanitary services	22 utilities
	Total = 6 + 7 + 8	Total = 38 + 51 + 22
Finance, insurance, real estate		52 finance and insurance
		53 real estate, rental, and leasing
	11 finance, insurance, and real estate	Total = 52 + 53
Service	13 business, auto and repair services	55 management of companies and enterprises
	14 personal services, excl. private HHs	
	15 entertainment and recreation services	71 entertainment and recreation services
	16 hospitals	
	17 medical services, excl. hospitals	62 health care and social assistance
	18 educational services	61 educational services
	19 social services	
	20 other professional services	54 professional, scientific, and technical services
		72 accommodation and food services
		56 admin support, waste management, and remediation services
		81 other services
		95 auxiliary services
		99 unclassified
	Total of service industry	Total = 55 + 71 + 62 + 61 + 54 + 72 + 56 + 81 + 95 + 99
Government	22 public administration	NA

Source: ARC classification in 20-county population and employment forecasts (ARC, 2005), at http://www.atlantaregional.com/regionaldata/2030forecast.html; (2) CPS classification can be traced in CPS Computer and Internet Use Supplement Technical File at http://www.census.gov/apsd/techdoc/cps/cpssep01.pdf. *Note*: Five of CPS industry categories cannot find a match in ARC data, including: 1 agriculture, 2 mining, 12 private households, 21 forestry and fisheries, and 23 armed forces.

Appendix B. Sensitivity analysis of computer ownership

To account for sampling and non-sampling errors, CPS suggests the formula below that produces a range that with 90% probability includes the average calculated for all possible samples^{x}:

$$90\%\ \mathrm{CI} = p \pm 1.645 \times \sqrt{(b/x)p(100 - p)} \tag{B.1}$$

where CI is the confidence interval of the percentage rate of computer ownership, b the parameters for computation of standard errors for internet and computer use estimates, September 2001. In the case of household computer ownership, Parameter b has a uniform value of 2068 for all types of households, x the base population (100% population of sample group), and p is the percentage rate of computer ownership.

As can be seen in Eq. (B.1), our estimation procedure requires data on the total number of households ("x") at each income level. However, US Census does not publicize income information for the unit of individual households. As a proxy, we resort to Census Summary File 3, which contains survey data but provides household income information, and calculate the household income distribution at the national metro level. We then locate the total number of households at the national metropolitan level, and multiply the percentage values at the national metro level to estimate the total number of households in each income group. Assuming the Atlanta metropolitan area shares the same household income structure as that of the national metropolitan area, we proceed with our calculations and derive the 90% confidence interval of each percentage rate of computer ownership in Table B1. Subsequently, we multiply each computer ownership rate to the number of corresponding group of households in Atlanta for estimation of lower and upper bound of computer stock. Following the same method, we conducted sensitivity analysis for business computer ownership; the results are shown in Tables B3 and B4.

See Tables B1–B4.

Table B1
The 90% confidence interval of HH computer ownership rate at national metro level in 2001

Family income (in 1999 US$)	No. of computers owned by households					
	3 or more		2		1	
	Lower	Upper	Lower	Upper	Lower	Upper
0–19,999	1.1	1.5	3.4	4.1	25.6	27.2
20,000–34,999	1.6	2.1	6.2	7.1	41.3	43.2
35,000–49,999	3.4	4.2	10.6	11.9	53.1	55.1
50,000–74,999	6.3	7.2	16.0	17.4	56.8	58.6
75,000 or more	14.4	15.6	25.0	26.5	49.8	51.5

Table B2
Household computer ownership range estimate in Atlanta metro in 2001

Family income (in 1999 US$)	Total computer stock		3 or more[a]		2[a]		1[a]	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
0–19,999	69,336	77,315	2,176	2,961	6,565	7,864	49,679	52,705
20,000–34,999	125,820	137,123	3,388	4,473	13,317	15,338	89,021	93,028
35,000–49,999	184,110	199,065	7,402	9,078	23,135	25,911	115,634	120,010
50,000–74,999	319,017	340,541	18,718	21,432	47,375	51,400	168,112	1,4324
75,000 or more	620,652	655,172	62,521	67,561	108,557	114,729	215,976	223,032
Total	1,318,935	1,409,216	94,205	105,505	198,949	215,241	638,422	662,219

[a] No. of computers owned by households.

Table B3
90% Confidence interval of computer use rate by industry in 2001

Industry classification by ARC	Computer use rate by industry (%)		
	Base estimate	Lower estimate	Upper estimate
Construction	27.37	26.14	28.61
Manufacturing	55.47	54.54	56.40
Transportation, communications, and utilities	54.27	53.07	55.47
Retail trade	39.63	38.71	40.55
Wholesale	61.39	60.04	62.75
Finance, insurance, and real estate	81.51	80.59	82.44
Service industry	63.48	63.02	63.94
Public administration	77.33	76.10	78.57

Table B4
Business computer stock estimate by industry in 2001

Industry classification by ARC	Estimated number of computers by industry (no.)		
	Base estimate	Lower estimate	Upper estimate
Construction	30,794	29,406	32,182
Manufacturing	102,117	100,405	103,829
Transportation, communications, and utilities	104,493	102,177	106,809
retail trade	147,983	144,545	151,420
Wholesale	110,570	108,128	113,012
Finance, insurance, and real estate	112,979	111,697	114,261
Service industry	585,400	581,183	589,617
Public administration	195,617	192,486	198,749
Total	1,389,953	1,370,027	1,409,879

Appendix C. Household computer ownership by age in Atlanta metro in 2001

See Table C1.

Table C1
Household computer ownership by age in Atlanta metro in 2001

	Estimated no. of computers owned by households by age				
	Seven or more years	5 years	3 years	New	Total
Base estimate	91,272	196,805	192,432	881,915	1,362,424
Lower estimate	88,359	190,523	186,289	853,764	1,318,935
Upper estimate	94,407	203,564	199,041	912,204	1,409,216

Source: Data is estimated based on the computer age profile summarized in Leigh and Realff (2003) and computer stock estimation discussed in Section 3 in this paper.

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