An Early Look at the Impact of Express Lane Eligibility on Medicaid and Children's Health Insurance Program Enrollment: An Analysis of the Statistical Enrollment Data System

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By

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Abstract

Express Lane Eligibility (ELE) has the potential to efficiently increase enrollment in Medicaid and the Children's Health Insurance Program (CHIP) by allowing state Medicaid and CHIP agencies to use data already acquired by other agencies to determine program eligibility. This report uses 2007 to 2011 quarterly data from the Statistical Enrollment Data System (SEDS) to measure the effects of ELE on total Medicaid and CHIP enrollment. SEDS is a web-based system maintained by CMS to collect Medicaid and CHIP enrollment data from states on a quarterly basis since 2000. During the period of analysis, eight states implemented ELE, ranging from policies that coordinate eligibility with the Supplemental Nutritional Assistance Program (Alabama, Iowa, Louisiana, Oregon, South Carolina), the National School Lunch Program (Louisiana, New Jersey, Oregon), or the Special Supplemental Nutrition Program for Women, Infants and Children (Georgia) to targeted outreach policies through income tax returns (Maryland, New Jersey). We estimate difference-in-difference equations (separate models for total Medicaid/CHIP enrollment and Medicaid only) with quarter and state fixed effects to measure the effect of ELE implementation on child enrollment, where the dependent variable is the natural log of enrollment in each state and quarter. The key independent variable is an indicator for whether or not the state had ELE in place in the given quarter, allowing the experience of matched non-ELE states to serve as a formal counterfactual against which to assess the changes in the ELE states. The model also controls for time varying factors within each state, such as the unemployment rate, population levels, Medicaid/CHIP eligibility changes, and the implementation of other state-level Medicaid/CHIP enrollment simplification policies. We estimate alternative model specifications to assess the robustness of the estimated ELE impacts and find significant evidence that ELE implementation increased Medicaid and Medicaid/CHIP enrollment. The estimated impacts of ELE on Medicaid enrollment were consistently positive, ranging between 4.0 and 7.3 percent, with most estimates statistically significant at the 5 percent level. Overall, these estimates had a central tendency of about 5.5 percent. The analyses also find evidence that ELE increased Medicaid/CHIP enrollment. Across a series of models, estimated impacts were again consistently positive, though less often statistically significant, with a central tendency of about 4.2 percent. Our results imply that ELE has been an effective way for states to increase new enrollment or improve the ease of retaining coverage among children eligible for Medicaid or CHIP.

Overview

Nearly 4.7 million uninsured children are eligible for Medicaid or the Children's Health Insurance Program (CHIP) (Kenney et al. 2010). Prior research attributes non-participation in Medicaid and CHIP—through low take-up or poor retention—to a host of factors, including lack of information about program eligibility, administrative hassle, and policy design complexities (Currie 2006; Remler and Glied 2003). To address some of these barriers, the Children's Health Insurance Program Reauthorization Act of 2009 (CHIPRA) gave states the option to implement Express Lane Eligibility (ELE) to help enroll and retain children who are eligible for Medicaid or CHIP but remain uninsured. States could also qualify for bonus payments provided they achieved target enrollment levels in Medicaid and implemented five out of a possible eight enrollment and retention policies, including ELE.

ELE policies allow state Medicaid and CHIP offices to use another agency's eligibility findings to qualify children for health coverage. States can choose from among 13 approved public agencies with which to partner or can obtain and use information directly state income tax returns.[1] ELE is regarded as a promising strategy for increasing enrollment in public coverage because so many low-income uninsured children's families participate in other government programs or file taxes: Kenney et al. (2010) estimate that ELE could reach 15 percent of eligible uninsured children who qualify for health coverage based on their

[1] States can also select an unlisted program that fits the statute's definition of an express lane agency (Centers for Medicaid and State Operations 2010)

participation in the Supplemental Nutrition Assistance Program (SNAP), while Dorn et al. (2009) estimate that 89 percent of uninsured children who qualified for Medicaid or CHIP in 2004 lived in families that filed federal income tax returns.

In contrast to other enrollment and retention policies that have common structural features across states (e.g., presumptive eligibility, continuous eligibility, elimination of asset requirements), ELE programs have additional features that vary across states: they can apply to initial eligibility determination or redetermination, they can apply to Medicaid alone, CHIP alone, or both programs, they can apply to any Medicaid/CHIP eligibility factor other than citizenship (e.g., income, residency, household composition, etc..), they can either include or dispense with the need to submit a separate application for health coverage, and they can utilize different levels of technology and automation. Because ELE represents a change to eligibility rules rather than a procedural innovation, ELE can be operationalized in many different ways, some of which may be more effective than others. Some ELE features have the potential to increase Medicaid/CHIP enrollment by raising families' awareness of their child's eligibility, while other features can reduce families' time and administrative burdens associated with applying or renewing. In addition, some ELE features can reduce states' administrative costs by eliminating duplication and paperwork.

This report uses 2007 to 2011 Medicaid and CHIP quarterly enrollment data available for all states through the Statistical Enrollment Data System (SEDS) to assess changes in Medicaid and CHIP enrollment in states after ELE implementation, using changes occurring over the same period in other states as a counterfactual. This impact analysis relies on multivariate models to account for possible confounding policy, demographic and economic changes, and time-invariant differences between ELE and non-ELE comparison states that may be driving Medicaid/CHIP enrollment changes and might otherwise be incorrectly attributed to ELE adoption or mask the effects of ELE. This is the first analysis of which we are aware that quantifies the impact of ELE policies adopted by eight states under CHIPRA. Prior studies have used descriptive or qualitative methods to examine the experiences of a single state (e.g., Louisiana in Dorn et al. 2012) or the experiences of early adopting ELE states (e.g., reviews of ELE policies in Alabama, Iowa, Louisiana, and New Jersey in Families USA 2011). In an ongoing descriptive study on ELE administrative costs and enrollment patterns, Orzol et al. (2012) analyze data on new Medicaid enrollment in New Jersey and Louisiana and new CHIP enrollment in Iowa through ELE and non-ELE pathways.

This report addresses the following questions:

- Does the implementation of ELE have a positive effect on Medicaid/CHIP enrollment? If so, how large are the enrollment gains?
- Does ELE have differential effects on Medicaid enrollment as opposed to CHIP enrollment?
- Are enrollment effects similar across different types of ELE programs?
- To what extent are enrollment effects robust within the subset of states that implemented ELE?
- If there are positive enrollment impacts, do they appear to be sustained over time?

The next sections provide background information on the ELE policies and on other economic and policy changes during the 2007 to 2011 period of analysis. Subsequent sections describe the data, methodological approach, and results. The concluding section summarizes the key findings, discusses the policy implications, and describes subsequent analyses to be undertaken in the coming year. Overall, we find that ELE increased Medicaid enrollment about 5.5 percent and combined Medicaid/CHIP enrollment by 4.2 percent.

Express Lane Eligibility Programs

As of June 2011, eight states had received Center for Medicare & Medicaid Services (CMS) approval of ELE state plan amendments (SPAs). As seen in Table 1, the ELE models adopted by these states included coordinating eligibility with the Supplemental Nutritional Assistance Program or SNAP (Alabama, Iowa, Louisiana, Oregon, South Carolina), the National School Lunch Program (NSLP) (New Jersey, Oregon), the Special Supplemental Nutrition Program for Women, Infants and Children (WIC) (Georgia), and state income tax returns (Maryland, New Jersey), as well as using ELE to automatically refer children between Medicaid and CHIP (Iowa). Below we briefly describe each program; Table 1 summarizes the programs, with a focus on the implementation assumptions used for the empirical analysis.

- Alabama uses findings from TANF and SNAP to establish income eligibility for Medicaid. Effective on October 1, 2009, the state's first ELE SPA applied to renewals only. The second, effective on April 1, 2010, extended this policy to initial applications. For both applications and renewals, state workers manually check TANF and SNAP income determinations to establish children's Medicaid eligibility. For the multivariate analysis, we use October 1, 2009 as the main ELE implementation date, but we also conduct a sensitivity analysis assuming an April 2010 implementation.

- Effective on January 1, 2011, Georgia's ELE program is the first in the country to partner with WIC, using that program's findings to establish income, state residence, and identity for initial applications to Medicaid and CHIP. WIC helps children age 5 and under, but the state is able to use WIC findings to qualify older children in WIC households for health coverage. Given Georgia's late implementation date relative to the other ELE states, there are only three post-ELE implementation quarters in the SEDS data that can be evaluated.

- Iowa implemented two ELE programs:

    - The first, effective in June 2010, uses SNAP findings to establish all Medicaid eligibility factors except citizenship and immigration status. This program applies to initial applications only. The state uses data matches between SNAP and Medicaid records to identify SNAP children who do not receive Medicaid. The families of such children are mailed notices of their Medicaid eligibility and given a chance to enroll by submitting a written request for health coverage, without the need to file a Medicaid application.

    - Iowa's second program uses ELE to make automatic referrals from Medicaid to CHIP. At both application and renewal, when a child is found ineligible by Medicaid because of income, the application/renewal is automatically referred to CHIP to support the child's continued coverage. This application of ELE was approved by CMS in July 2010, but Medicaid and CHIP have been using this method of referral dating back to 2004.

- Louisiana uses ELE to qualify children for Medicaid based on SNAP determinations of income, state residence, Social Security Number, and identity. After data matches identified children who received SNAP but not Medicaid, the parents of such children were sent Medicaid cards and given an opportunity to consent to enrollment by using those cards to seek care. This initiative began in February 2010, with eligibility retroactive to December 2009, and state officials claim to have automatically enrolled approximately 10,000 children through ELE in Medicaid in February 2010 (Dorn et al. 2012; Orzol et al. 2012). Automatic renewal of children's Medicaid eligibility based on receipt of SNAP was first taken to scale in November 2010. In 2011, the state changed its approach to ELE applications by asking parents to consent to ELE enrollment by checking a box on the SNAP application, rather than by using a Medicaid card to seek care. The main empirical model assumes a February 2010 implementation date, but we also estimate a model that assumes ELE was in effect in December 2009.

- Oregon uses SNAP and NSLP findings to establish income-eligibility and state residence for Medicaid and CHIP initial applications. The SNAP initiative was effective statewide in September 2010. Operating as a pilot project in four districts, the NSLP effort began in November 2011. When data matches show that children receive SNAP or NSLP but not health coverage, families are sent a simplified ELE form, which can be completed by mail or phone to enroll in Medicaid or CHIP.

- In April 2011, South Carolina began redetermining Medicaid eligibility based on SNAP and TANF findings about income and assets, reducing the need to obtain information from families before renewing coverage. After using manual procedures to make these renewals for April and May 2011, the state shifted to a fully automated process. Given the implementation date, there are only two post-ELE implementation quarters in South Carolina.

- Finally, two states—New Jersey and Maryland—have ELE programs that work through income tax returns. Both states changed their income tax returns to ask parents to identify their uninsured dependents.

    - New Jersey uses income tax data to establish identity and income (except for the self-employed, who must complete a standard application). Parents whose tax returns flagged their children as uninsured are sent streamlined ELE application forms, which they must complete and return to obtain an eligibility determination. Operational since May 2009, the program is authorized for Medicaid and CHIP applications and renewals, although state officials report that they are only using ELE for initial applications at this point. New Jersey also has an ELE pilot program through NSLP.

    - For initial applications, Maryland uses state income tax data to establish state residence for Medicaid purposes. Families who identify their children as uninsured on tax returns and who appear potentially income-eligible are sent application forms that they must complete and return, providing the same income information that is requested from all Medicaid applicants. Before implementing ELE in April 2010—indeed, before the passage of CHIPRA—Maryland was already using the state income tax process as a targeted outreach tool. Beginning in September 2008, the state sent Medicaid application forms to parents who appeared income-eligible and who identified their children as uninsured on 2007 tax returns. We assume, for evaluation purposes, that Maryland's ELE program was implemented when the state began tax-based outreach during the first fiscal quarter of 2009, but we also estimate models assuming ELE implementation on April 1, 2010.

Changes in the Economy and Medicaid and CHIP Policies

As indicated above, the multivariate analysis accounts for changes in economic conditions and Medicaid and CHIP policies outside ELE that might otherwise bias estimates of the ELE effect. The main period of analysis, fiscal Q1 2007 to Q4 2011, is dominated by a recession that began in 2007, when unemployment rose, real personal income fell, and more people were living in families without a full-time worker. Economic conditions between 2009 and 2011 stabilized but remained poor relative to conditions before the recession (Holahan and Chen 2011).

The loss of coverage during economic downturns, such as during the most recent recession, is linked to declines in employment, and thus loss of employer-sponsored coverage. Not surprisingly, prior research has found strong links between the unemployment rate and the overall loss of coverage (Cawley and Simon 2003; Cawley et al. 2011; Holahan and Garret 2009). However, Medicaid and CHIP enrollment increases offset some losses in private coverage. In fact, the uninsured rate among children has declined slightly in recent years due to increased enrollment in Medicaid and CHIP (Blavin et al. 2012; Holahan and Chen 2011). Our multivariate analysis is designed to take into account the changing economic conditions during the period of analysis by controlling for changes in each state's unemployment rate and personal income.

From 2007 to 2011, several states expanded Medicaid/CHIP eligibility to higher income children and introduced changes to their enrollment and renewal processes, mostly aimed at reducing the number of children who are eligible for Medicaid and CHIP but remain uninsured (Heberlein et al. 2012). Our main analysis controls for Medicaid/CHIP eligibility changes, joint application for Medicaid and CHIP, presumptive eligibility, administrative verification of income, elimination of in-person interviews, elimination of asset test requirements, and continuous eligibility. Prior research findings conclude that these enrollment and renewal simplifications can promote enrollment and continuous coverage (Wachino and Weiss 2009). Without controlling for changes in these policies, Medicaid/CHIP enrollment increases during the period of analysis might be incorrectly attributed to ELE. Changes to these Medicaid/CHIP policies among ELE and non-ELE states are described in appendix A.

Data

SEDS Data

SEDS is a web-based system maintained by CMS since 2000 that collects new and total Medicaid and CHIP enrollment data from states on a quarterly basis. States must submit quarterly enrollment data within 30 days after the end of the fiscal quarter and aggregate annual data within 30 days after the end of the fourth quarter.[2] This analysis uses quarterly and annual total enrollment data from three of the SEDS reporting forms and to our knowledge, this is the first analysis to do so:[3]

- ***Form CMS-64EC*** collects data on children enrolled in the Medical Assistance Program—that is, Title XIX-funded Medicaid coverage or traditional Medicaid
- **Form CMS-64.21E** collects data on children enrolled in Medicaid expansion CHIPs—that is, Title XXI-funded Medicaid coverage.

[2] Federal fiscal year quarters are as follows: first quarter, October 1 through December 31; second quarter, January 1 through March 31; third quarter, April 1 through June 30; and fourth quarter, July 1 to September 30.

[3] All data files were downloaded in January 2012. There were also smaller state-specific downloads through March 2012, as some states revised their enrollment data.

- ***Form CMS-21E*** collects data on children enrolled in separate child health programs (CMS 2011).

This report focuses on the 2007 to 2011 quarterly SEDS data on total enrollment (the unduplicated number of children ever enrolled during the quarter). Throughout the analysis, we define Medicaid enrollment to include both traditional Medicaid and Title XXI CHIP-funded Medicaid expansions, sometimes called M-CHIP. We define total Medicaid/CHIP enrollment to include enrollment in traditional Medicaid, CHIP-funded Medicaid expansions, and separate CHIP (sometimes called S-CHIP). Quarterly data prior to 2007 are excluded due to reporting errors and high item nonresponse rates.[4] As a supplemental analysis, appendix C highlights enrollment annual trends among ELE and non-ELE states over a longer timeframe (2000 to 2011) and includes a multivariate test to help validate the findings from the main quarterly analysis.[5]

Some quality issues are evident in the total enrollment data, including missing observations and likely reporting errors. We obtained a clean version of the 2000 to 2010 annual SEDS data that was edited and approved by CMS for prior analyses, and updated it with new 2011 data and revised 2010 data from some states. We addressed quality issues in the quarterly data by imputing missing values and repairing reporting errors on a case-by-case basis.

[4] We analyzed the 2005 and 2006 SEDS quarterly data but found a number of problems. Most noticeably, two of the ELE states (Alabama and Georgia) did not report quarterly data during these years.

[5] Given our focus on the evaluation of ELE policies, the annual SEDS data are problematic due to the imprecision introduced with respect to the definition of the pre and post-ELE implementation time periods and an insufficient number of post-ELE implementation years. As such, this analysis primarily relies on quarterly enrollment data to give us enough data points to capture the potential impact of ELE.

Our imputation strategy, which uses interpolation in most instances, is consistent with procedures that Mathematica developed while working with the annual SEDS data (Ellwood et al. 2003).[6] Data points were also cross-validated using the Medicaid Statistical Information System and monthly Medicaid/CHIP enrollment data reports from the Kaiser Commission on Medicaid and the Uninsured (Kaiser 2011a; Kaiser 2011b). We made imputations on less than 5 percent of state-quarter observations and the final analysis file, with the imputations, was approved by CMS-SEDS analysts on March 30, 2012.

Two non-ELE states, Maine and Montana, are excluded from this analysis due to concerns about data reliability. Maine implemented a new Medicaid Management Information System in 2011 and identified problems in their enrollment data caused by reporting errors. They are currently working on this problem, but are not expected to submit revised data any time soon.[7] Similarly, we found substantial variation in the Montana data from 2007 to 2011, although patterns in the 2009 to 2011 data could be partially explained by Medicaid/CHIP expansions and changes in economic conditions, according to the CMS Regional Office.[8] We also conducted several statistical tests (for example, difference in fit, a diagnostic meant to show how influential a point is in a statistical regression) and determined that Montana was an outlier state, which indicated that it might not serve as an accurate counterfactual to ELE states. While Montana had some influence on the regression model in the multivariate analysis,

[6] For instance, if data from a particular quarter were missing or inconsistent, we averaged data from the previous quarter and the subsequent quarter. If states had more than one quarter of missing data, we allocated the difference between the last reported quarter and the next reported quarter evenly over the missing quarters. Edited cases were cross-validated with other data sources where possible.

[7] E-mail correspondence with Jeffery Silverman, CMS contact person for SEDS, on March 30, 2012.

[8] Ibid.

we found that our main results did not substantively change by its inclusion or exclusion. However, given the outlier tests and uncertainty over the validity of the state's data, we excluded Montana from the descriptive and multivariate analyses.

Finally, this report uses total enrollment as opposed to new enrollment data for two major reasons. First, we found a number of major data quality problems with the new enrollment data, which could not be resolved during the first year of this analysis. Annual new enrollment data are unavailable before 2009 because states were not required to submit this information, and the currently available data from 2009 to 2011 are unusable due to a large number of nonresponses. Second, the total enrollment data captures ELE's effect on Medicaid/CHIP enrollment via initial eligibility determination and improved retention, whereas the new enrollment data would only capture ELE's impact on initial eligibility determination. As discussed in the prior section and displayed in table 1, some ELE programs cover initial determination and redetermination, some cover initial determination only, and one ELE program covers redetermination only (South Carolina). Future research can aim to separate the effects of ELE at initial application and renewal.

Supplemental table S.1 contains the Medicaid and CHIP quarterly enrollment data for all ELE states from 2007 to 2011, and table S.2 contains the Medicaid and CHIP annual enrollment data for all ELE states from 2000 to 2011. Imputed enrollment values are noted.

Additional Data Sources

The multivariate analysis accounts for many variables, such as changes in economic conditions and in various non-ELE enrollment policies that might otherwise bias the estimates of ELE's effects. To construct these variables, we draw on a number of data sources:

- Quarterly state unemployment rate data from the Bureau of Labor Statistics (Bureau of Labor Statistics 2012).
- Child state population estimates from the U.S. Census Bureau (U.S. Census Bureau 2012).
- Quarterly state personal income from the Bureau of Economic Analysis (Bureau of Economic Analysis 2012).
- Annual state Medicaid and CHIP eligibility rules for parents and children from the Urban Institute's Medicaid eligibility simulation model and the Kaiser Family Foundation.
- Implementation dates of various state policies that influence the ease of new enrollment into Medicaid or CHIP, from publications from the Kaiser Commission on Medicaid and the Uninsured and the Georgetown Center for Children and Families (Cohen-Ross et al. 2007; Cohen-Ross et al. 2008; Cohen-Ross et al. 2009a; Cohen-Ross et al. 2009b; Heberlein et al. 2011; Heberlein 2012). We assumed implementation during the second quarter of the fiscal year when we could not find the exact implementation date for a given policy. We selected the following Medicaid and CHIP policy covariates based on data quality, the ability to characterize the policy change in a quantitative analysis, the number of program changes observed during the period of analysis to ensure sufficient degrees of freedom, and prior evidence on the policy's potential impact on Medicaid/CHIP enrollment (e.g., policies documented in Wachino and Weiss 2009): joint application for Medicaid and CHIP, presumptive eligibility, administrative verification of income, no in-person interview, elimination of asset test, and continuous eligibility. We did not include the elimination of an asset test in Medicaid because no state in our sample made changes to this policy during the period of analysis. Table 2 highlights aggregate changes in these policies during the period of analysis, and the appendix A describes state-specific changes.
- Finally, we use the 2011 Current Population Survey to create 'simulated' adult and child eligibility variables consistent with the method developed by Cutler and Gruber (1996). This method applies each state's eligibility thresholds to a standardized national sample of parents and children, as opposed to a particular state's own population, removing time-variant factors and differences in the income distribution across states. The derived eligibility variables capture the

generosity of each state's eligibility criteria and are not confounded by varying conditions across or within states over time.

Methods

This report includes descriptive analyses of the SEDS data as well as a multivariate regression analyses that examines whether there is evidence of a causal link between ELE and Medicaid/CHIP enrollment. The main descriptive analysis examines enrollment trends in Medicaid and CHIP drawing on the SEDS quarterly data from 2007 onward. Through this analysis, we compare Medicaid and CHIP enrollment trends between ELE states and the non-ELE states and identify any noticeable spikes in enrollment in ELE states following their implementation of the policy. A supplemental analysis (reported in appendix C) uses the annual SEDS data from as far back as 2000 to examine longer time-trends in enrollment.

Multivariate Analysis: The Main Model

Using 2007 to 2011 quarterly SEDS data, we estimate separate regression models for total Medicaid/CHIP enrollment and for Medicaid enrollment only, where the dependent variable is the log transformation of children's enrollment in each state and quarter.[9] We estimate two-way fixed effect difference-in-difference equations with balanced panels as our main models

[9] We also estimate a model restricted to separate CHIP programs only, but this model is limited by a smaller sample size and much smaller number of enrollees in each state. This is further discussed in the results section. Appendix C includes different models where the unit of analysis varies by state and year, but, as we indicated above, we primarily rely on the quarterly data to maximize the number of post-ELE implementation periods and to measure the pre and post periods with more precision.

for this analysis, where the eight ELE states constitute the treatment group (with the intervention occurring at different points in time) and matched non-ELE states with similar pre-2009 enrollment trends comprise the comparison group. The main estimation equations are:

$$Log(McaidCHIP)_{i,t} = \propto + \beta_1 ELE_{i,t} + \beta_2 OTHERPOLICY_{i,t} + \beta_3 COVARIATES_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t} \quad (1)$$

$$Log(Medicaid)_{i,t} = \propto + \beta_1 ELE_{i,t} + \beta_2 OTHERPOLICY_{i,t} + \beta_3 COVARIATES_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t} \quad (2)$$

Where $\propto$ is the intercept term, *i* is an index for state, t is an index for unique quarter, γ_i is a set of state dummy variables (state fixed effects), δ_t is a set of quarter-specific dummy variables (quarter fixed effects), and $\epsilon_{i,t}$ is a random error term. The dependent variable, $Log(McaidCHIP)_{i,t}$, is the log of the number of children ever enrolled in Medicaid or CHIP in state *i* during quarter *t,* and $Log(Medicaid)_{i,t}$ corresponds to the number of children ever enrolled in Medicaid. We log transform enrollment so that the dependent variable has a normal distribution; otherwise the distribution of the untransformed variable is heavily skewed. We report robust standard errors clustered at the state-level to correct for possible heteroskedasticity and autocorrelation (White 1980; Bertrand, Duflo, and Mullainathan 2004).

The key independent variable of interest is $ELE_{i,t}$, which is set to one when the observation is an ELE state and the quarter either contains the month when ELE was implemented or is after ELE implementation. This variable measures the effects of ELE on Medicaid/CHIP or on Medicaid-only enrollment, depending on the model. With a log transformed dependent variable, the estimated ELE coefficient reflects the percent change in total enrollment associated with ELE implementation. We anticipate that ELE will have a positive impact on Medicaid/CHIP enrollment—that is, β_1>0.

Compared to the simple descriptive comparisons, findings from this model offer far more rigorous evidence of the effects of ELE because they control for many sources of potential confounding factors. The state fixed effects $\gamma_i$help control time-invariant differences across states that could be correlated with the ELE variable, such as inherent differences between ELE-states and non-ELE states e.g., potential differences in reporting accuracy of the SEDS data. The quarter fixed effects δ_t control for factors common to all states that vary from quarter to quarter.

By including indicators for other state policy changes and time-varying covariates, we control for other factors that change over time, which could also contribute to differences in aggregate Medicaid and CHIP enrollment numbers. $OTHERPOLICY$ is a series of state-policy variables, and $COVARIATES$ is a series of other state-level controls that vary over time and that could influence Medicaid/CHIP enrollment. In combined Medicaid/CHIP model (1), $OTHERPOLICY$ includes the simulated Medicaid/CHIP eligibility threshold for children,[10] the simulated Medicaid eligibility threshold for parents, and dummy indicators for the presence of a separate CHIP program, joint applications for Medicaid and CHIP, presumptive eligibility for Medicaid, administrative verification of income for Medicaid, no in-person interview for

[10] The simulated CHIP eligibility threshold is used for states with separate CHIP programs and the simulated child Medicaid eligibility threshold is used for all other states. In sensitivity models where we focus on separate CHIP only, $COVARIATES$ includes the CHIP eligibility threshold and CHIP-specific administrative simplification dummy variables.

Medicaid, continuous eligibility for Medicaid, presumptive eligibility for CHIP, administrative verification of income for CHIP, no in-person interview for CHIP, elimination of asset test for CHIP, and continuous eligibility for CHIP. In the Medicaid only model (2), we use the simulated child Medicaid eligibility threshold and do not include the CHIP-specific policy dummy variables. In the main specification, $COVARIATES$ includes the state-quarter specific unemployment rate and year-state child population estimates that are log transformed. The state income measure is included in a sensitivity analysis as described below. We do not lag any of the policy or economic variables in the main specification of the model, but do so as part of the sensitivity analysis.

Choosing Comparison States

Difference-in-difference models only provide consistent estimates of the treatment effect, if in the absence of the policy intervention, the time path in the outcome is the same for both the treatment and comparison states (Meyer 1995). For example, if Medicaid enrollment is trending upwards (downwards) at a faster rate within the comparison group relative to the ELE states, the difference-in-difference model will understate (overstate) the benefits of ELE implementation. Given the widespread variation in Medicaid/CHIP participation, enrollment, and policies across states, we anticipate that some non-ELE states will have similar trends in enrollment compared to ELE states, while others will have dissimilar trends.

Using a similar method as Lien and Evans (2005), we choose comparison states that had similar pre-ELE trends in Medicaid and Medicaid/CHIP enrollment trends as the ELE states. Since the first ELE program was implemented in 2009, we focus on trends in the 2007 and 2008 quarters prior to adoption of ELE. To select the comparison states, we estimate models similar to (1) and (2) that include a time trend and time trend interacted with an "ELE state" indicator. We include one non-ELE state at a time and test if the average trend among ELE states differs from the trend for that non-ELE state. If we reject the hypothesis at the 5 percent level that the coefficient associated with the interaction term equals zero, we exclude the non-ELE state from the sample, thus increasing the likelihood of choosing comparison states that possess a similar trend in Medicaid or Medicaid/CHIP enrollment as the average treatment state prior to ELE implementation.

The final Medicaid model includes 33 comparison states and the final Medicaid/CHIP model includes 25 comparison states. In the Medicaid model, we exclude Arizona, Colorado, Illinois, Nevada, New Mexico, Virginia, Washington, and Wyoming from the comparison group. In the combined Medicaid/CHIP model, we exclude Arizona, California, Connecticut, Florida, Illinois, Indiana, Kentucky, Missouri, Nevada, New Mexico, North Dakota, Ohio, Tennessee, Texas, Virginia, and Washington. Maine and Montana are also excluded from both models.

Sensitivity Tests

We conduct a series of robustness checks to explore the consistency of the ELE parameter estimates. To the extent that these estimates display consistency, it strengthens the evidence provided by the original model specification and, thereby, the conclusions that can be drawn from the analysis. These robustness checks include re-estimating the main model with the following variants:

- Alternative specifications of the control variables to determine the source of the ELE effect:
  - To start, we remove the policy variables, unemployment rate, and child population from the main model specification (i.e., this model includes only state and quarter fixed effects). This simple unadjusted difference-in-difference model removes all time-varying covariates and approximates the average ELE treatment effect from the descriptive data, relative to the chosen set of comparison states (alternative 1).
  - We then add the policy variables to the simple model (all at once and each individually) to determine if their inclusion alters the magnitude and significance of the ELE variable (alternative 2).
  - We also add the unemployment rate and child population variables to the simple model to determine if their inclusion alters the magnitude and significance of the coefficient on the ELE variable (alternative 3).
  - We replace all of the administrative simplification dummy variables with a policy index, ranging from 0 to 5 in the Medicaid model and 0 to 10 in the Medicaid/CHIP model (alternative 4).
- Alternative specifications with respect to how the comparison group is defined, excluding non-ELE states in a systematic manner to determine if specific control states are driving the main results. These tests are important because the non-ELE states control for what the baseline trend in Medicaid/CHIP enrollment would have been in the absence of ELE.
  - We include all 41 non-ELE states as the comparison group in the Medicaid/CHIP and Medicaid models (alternative 5).
  - We use the same methodology from the main model to select comparison states, but exclude non-ELE states where the time trend interaction term is statistically significant at the 10 percent level (alternative 6) and at the 1 percent level (alternative 7). In the Medicaid/CHIP model, there are 22 comparison states in alternative 6 and 35 in alternative 7, compared to 25 in the main model. In the Medicaid only model, there are 30 and 36 comparison states in alternatives 6 and 7, respectively, compared to 33 in the main model.
  - We use a similar but more restrictive method to select comparison states (alternative 8). Instead of interacting the ELE indicator with the time trend, we interact each quarter dummy with the ELE state variable and exclude non-ELE states where we reject the null that the joint interaction terms are zero at the 5 percent level. This method increases the likelihood of choosing comparison states that have the same quarter-to-quarter pattern in enrollment before 2009 and excludes more comparisons states relative to the main model scenario. Under this alternative, there are 15 comparison states in the Medicaid/CHIP model and 19 comparison states in the Medicaid model.
  - We exclude non-ELE states that are statistical outliers and might not serve as ideal comparison states. For this exercise, we remove non-ELE states that had

observations with studentized residuals greater 2.5 and less than -2.5 in the main model (alternative 9).[11]

  - Similarly, we re-estimate the simple unadjusted Medicaid/CHIP and Medicaid only difference-in-difference models, including one non-ELE state at time to determine which comparison states have the strongest influence on the ELE coefficient magnitude. We then rank the states based on the estimated ELE coefficient when they are included in the model and re-estimate the main model, excluding the comparison states that resulted in the 5 highest and the 5 lowest ELE effects, respectively (alternative 10). We also estimate a variant that excludes comparison states with the 10 highest and 10 lowest ELE effects (alternative 11).
- Using alternative implementation dates for certain states, such as Alabama (alternative 12), Maryland (alternative 13) and Louisiana (alternative 14), where, as indicated above, the ELE changes were phased in.

We also discuss several other alternative models to support the robustness of the ELE variable, but the results are not included in tables.[12] These robustness checks include re-estimating the main model with the following variants:

- Estimating Newey-West heteroskedasticity and autocorrelation robust standard errors as opposed to cluster-robust standard errors. Rather than specifying a cluster variable, the Newey-West variance estimator requires a specification on the maximum order of any significant autocorrelation in the disturbance process. While the Newey-West method yields smaller standard errors and might be biased downwards relative to the cluster-robust standard errors in our main model specification, in some cases, the selection of a less robust covariance matrix estimator (e.g., Newey-White) in favor of the more robust estimator (cluster-robust) can improve the quality of inference about regression parameters and increase the power of hypothesis tests (Packalen and Wirjanto 2012). As such, other difference-in-differences studies (e.g., Klick and Stratmann 2007) have reported both sets of standard errors for each coefficient.
- Different dependent variable specifications, such as enrollment without the log transformation and defining enrollment as a percent of the total child population); for the latter, the numerator (enrollment) comes from the SEDS and varies by state-quarter, whereas the denominator (child population) comes from the Bureau of the Census and

[11] In the total Medicaid/CHIP model, we removed the following 8 states in addition to Montana and Maine: North Dakota, Illinois, District of Columbia, Kansas, Utah, Hawaii, Nevada, and New York. In the total Medicaid only model, we removed the following 9 states in additional to Montana and Maine: North Dakota, Illinois, District of Columbia, Kansas, Utah, Hawaii, Nevada, Colorado, and Idaho.

[12] These results are available upon request.

only varies by year. However, this model can predict out-of-range values (below 0 or above 1) and assumes a linear relationship, even though the dependent variable is sigmoidal (Long 1997) which is why we did not use it as our main specification.

- Lagging all of the control variables by 1 and 2 quarters.
- Including additional controls for recent CHIPRA policy options. We include a control for whether or not the state expanded coverage to children who have been lawfully residing in the U.S. for less than five years under the new CHIPRA option.[13] We also add controls for the receipt of Cycle I (awarded September 2009) or Cycle II (August 2011) CHIPRA outreach grants.[14]
- Including year fixed effects instead of quarter fixed effects and time trend (a variable that takes the value one in the first quarter of 2007, two in the second quarter of 2007, etc.) instead of quarter fixed effects.
- Adding controls for quarter-state personal income and the adult population.
- Re-specifying the Medicaid/CHIP adult and child eligibility variables as non-linear (e.g., log transformed).
- Weighting by the state's population.
- Using 2006 to 2011 annual SEDS as opposed to quarterly data (appendix C). This model helps validate the findings from the quarterly data, but is limited by a smaller sample size and fewer degrees of freedom.
- Estimating falsification models. As a placebo law, we create an ELE 'lag' variable set to one in the four quarters prior to each state's actual implementation date and zero otherwise. We also created a similar two-year lag variable. We estimate the main models, substituting the ELE 'lag' variables for the main ELE variable, and find no evidence of a positive "ELE placebo" effect in the one or two years prior to actual implementation.

Characterizing ELE effects

Any attempt to characterize the effects of ELE must be seen in the context of a policy that can vary widely in both its implementation and target population. This underscores the importance of assessing the effects of ELE within individual or small groups of states, as a way to best understand the ELE models that may be most effective. In order to do so, we created different

[13] Prior to CHIPRA in 2009, immigrant children could not be covered with federal Medicaid or CHIP funds during the first five years of legal residence. As of January 1, 2012, almost half of the states (24, including DC) adopted the option to cover immigrant children without the five-year waiting period.

[14] We tested several variable specifications, including dummy variables to control for whether or not the state received any outreach dollars and amount of outreach dollars that were dispersed to the state.

ELE policy variables—"ELE through SNAP" and "ELE through tax returns"—to explore whether there appeared to be a differential effect based on the type of ELE program implemented, but as indicated below, our ability to make such an assessment is constrained by the limited experience with ELE to date. We also re-estimate the main model excluding one ELE state at a time to determine if the overall effect is primarily driven by the ELE experience in single state or if the ELE effect seems to vary across states. Similarly, we estimate state-specific models in which we define a unique set of comparison states with similar pre-ELE enrollment trends. We used the same method to select the comparison states as we did in the main model, but each model is estimated on the pre-ELE period specific to each ELE state, providing a more accurate reflection of enrollment trends prior to ELE implementation within that state. While we do not place much emphasis on the individual impact estimates derived for each state, these models help validate the robustness of the main results and use a more accurate set of comparison states specific to each ELE state.

We also assess whether ELE works instantaneously or gradually, by estimating a model that interacts the main ELE variable with a "number of quarters since ELE adoption" variable (set to 0 for pre-ELE implementation and for non-ELE states). However, such assessments are challenging because there is a limited sample of ELE states and of post-implementation periods, which reduces the degrees of freedom for detecting differences between pre- and post-ELE enrollment for different ELE approaches and different post-ELE time periods.

Results

Descriptive Analysis of SEDS Data

From 2007 through 2011, total Medicaid/CHIP enrollment increased substantially among both ELE and the 41 non-ELE states (data not shown). Total Medicaid/CHIP enrollment among all eight ELE states increased from 4.18 million to 5.15 million from the first fiscal quarter of 2007 to the last fiscal quarter of 2011, representing an increase of 23 percent. The remaining 41 non-ELE states experienced a fairly comparable percentage increase in Medicaid/CHIP enrollment over the same period, with aggregate enrollment increasing by 24 percent, from 25.0 to 31.1 million. Medicaid enrollment growth from 2007 to 2011 among ELE states was 2 percentage points higher than the growth rate among non-ELE states. Separate CHIP enrollment among non-ELE states steadily increased over the period as well, but CHIP trends among ELE states varied, as described below.

Figures 1a and 1b show the trends in average Medicaid/CHIP and Medicaid enrollment among the eight ELE states, the chosen comparison states, and the excluded non-ELE states. In both figures, it's clear that the ELE states and comparison states had comparable enrollment trends prior to 2009; the average 2007-2008 quarterly growth rate was approximately .4 percent among the ELE states and comparison states in the Medicaid model (Figure 1a) and .3 percent in the Medicaid/CHIP model (Figure 1b). Although it is difficult to see in the figures, average enrollment grew at a faster rate among the ELE states relative to the comparison states from 2009 to 2011. Moreover, the simple difference-in-difference model, which includes only state and quarter dummy variables (described below in the multivariate results section), also indicates that ELE states had higher enrollment growth after they implemented ELE relative to before they implemented ELE, compared to the changes in enrollment growth found in the non-ELE comparison states.

The ELE states and comparison states had similar enrollment trends prior to 2009 because we systematically excluded non-ELE states with significantly different trends. Figures 1a and 1b also highlight how enrollment increased at a faster rate among the excluded states in the pre-2009 period compared to the ELE states and comparison states. As discussed above, the average 2007-2008 quarterly enrollment growth rates among the ELE states and comparison states was close to zero. In contrast, the average 2007-2008 quarterly enrollment growth rate was 1.4 percent among the excluded states in the Medicaid model and 1.3 percent among the excluded states in the Medicaid/CHIP model. This upward trend in enrollment continued in the post-2009 period, which could lead us to understate the benefits of ELE if these states were included in the comparison group.[15]

Multivariate Regression Results

[15] Appendix B provides a summary of the descriptive quarterly data in each ELE state and compares the findings to the monthly administrative data on enrollment through ELE in Louisiana, Iowa, and New Jersey, as presented by Orzol et al. (2012). Using a simple pre-post comparison and ignoring the trends in comparison states, few noticeable spikes or trend changes are evident in Medicaid enrollment among any of the eight ELE states or in CHIP enrollment among any of the four states adopting ELE for CHIP (Iowa, Oregon, Georgia, and New Jersey).

Findings from the main multivariate difference-in-difference models show statistically significant evidence of a positive effect of ELE on enrollment (Table 3). On average, the main model, which uses the designated sets of comparison states described above, indicates that ELE implementation increased combined Medicaid/CHIP enrollment by 4.2 percent (statistically significant at the 10 percent level) and Medicaid enrollment by 5.6 percent (statistically significant at the 5 percent level), holding all other observed policy and economic changes constant. These results imply that ELE had a larger effect on Medicaid enrollment than on enrollment in separate CHIP programs.

We also estimated separate models with the four states (Georgia, Iowa, New Jersey, and Oregon) with ELE through CHIP as the treatment group and various groupings of non-ELE states (e.g., states with similar pre-2009 CHIP enrollment trends) with a separate CHIP as the comparison group.[16] The ELE coefficient varied in magnitude across all of the model specifications and we did not find any evidence that that the ELE programs through CHIP had a statistically significant effect on separate CHIP enrollment. However, these results could be attributable to insufficient power as the sample size and potential ELE effect size are more limited in the separate CHIP models.

Sensitivity Analyses

Across a series of alternative models that address different potential sources of specification error and bias (Table 4), we consistently find a positive estimated ELE effect, supporting the

[16] Including Alabama and Louisiana in the model—states with separate CHIP but with ELE through Medicaid only—as part of the control group does not influence the results.

findings from the main model. In all of the alternative models in table 4, the ELE coefficient remains positive with a central tendency that is close to what we find in the main model; we find that the magnitude associated with the ELE variable in the total Medicaid/CHIP model ranges from 2.8 to 4.8 percent, with a median of 3.8 percent, and in the Medicaid only model ranges from 4.0 to 7.3 percent, with a median of 5.5 percent. For all of the other models where the results are not shown, we find that the ELE effect is also close to what we find in the main model.

While remaining consistently positive, however, we do find that the statistical significance of the estimated ELE effect varies across the model specifications. The estimated ELE coefficient in the basic unadjusted difference-in-difference model (alternative 1) is still similar in magnitude to the main fully adjusted model result, but is not statistically significant (p-value=.11 in the Medicaid model and .20 in the Medicaid/CHIP model). Alternatives 2 and 4 show that controlling for differential policy changes among ELE states and the comparison group strengthens the precision of the estimated effect, but that the inclusion or exclusion of the policy variables are not driving the magnitude and direction of the ELE variable in the main model.

We also find that the ELE effect is slightly smaller in magnitude and statistically insignificant (p-value=.12 in the Medicaid model and .14 in the Medicaid/CHIP model) when we use all 41 non-ELE states as the comparison group, as opposed to using states with similar pre-ELE enrollment trends (alternative 5). However, the estimates of the ELE effect from this model could be biased downward because they include comparison states with quarterly enrollment levels trending upwards relative to ELE states during the pre-implementation time period. We also find that the ELE effect in the Medicaid model is statistically significant in all of the remaining comparison group sensitivity models (alternatives 6 through 11), whereas the ELE coefficient in the Medicaid/CHIP model is statistically significant in only two of these six alternatives.

Appendix D contains a more detailed discussion of each alternative and describes how these results raise confidence in the direction of the ELE effects found in the main Medicaid model, but introduces some uncertainly about the underlying impact in the combined Medicaid/CHIP model.

Findings on other Variables

According to the results in the main models, the log transformation of the child population has a positive and statistically significant effect on enrollment as expected (Table 3). These results imply that a 1 percent increase in a state's total child population would yield a .86 percent increase in quarterly Medicaid/CHIP enrollment and a 1.21 percent increase in Medicaid enrollment on average, holding all else constant. The coefficient on the unemployment variable is 0.007 in the Medicaid/CHIP enrollment model and 0.005 in the Medicaid only model, but is statistically insignificant in the models in which the standard errors are clustered at the state level.

The remaining variables control for observed changes in Medicaid/CHIP policy during the period of analysis. We find that administrative verification of income increases Medicaid enrollment by approximately 6.4 percent (statistically significant at the 1 percent level), holding all else constant. None of the other policy variables are statistically significant at conventional levels in the main model. Moreover, the estimated policy effects vary in magnitude and statistical significance depending on the model specification.

Characterizing the ELE effects

The results in table 5 suggest that the ELE effect on Medicaid/CHIP and Medicaid enrollment varies across states. When we re-estimated each of the main models excluding one ELE state at a time, we find that the coefficient on the ELE variable is smaller in magnitude (compared to the main effect) when Iowa, Maryland, New Jersey, and Oregon are excluded, suggesting that the ELE effect may have been stronger in these four states. The ELE effect is no longer statistically significant at conventional levels when these four states are individually removed from the Medicaid/CHIP model, whereas in the Medicaid model, only the exclusion of Oregon eliminates the statistical significance associated with the ELE coefficient (p-value=.12). However, the ELE effect in the Medicaid model remains statistical significant when Oregon is removed from some of the alternative model specifications that alter the composition of comparison states, such as alternatives 9 and 10. Altogether, this suggests that no single state's experience is driving the average effect in the Medicaid model.

Similarly, the ELE coefficients are positive and statistically significant in both the Medicaid only and combined Medicaid/CHIP models, with magnitudes exceeding the average effect, when Iowa, Maryland, New Jersey, and Oregon are included in the sample one at a time. We also find a smaller, but statistically significant effect, for Alabama in the Medicaid only model. In contrast, there is no evidence in favor of a positive ELE effect on enrollment when the other ELE states are included one at a time. These results hold when we use the main model comparison states and the comparison states specific to each ELE state. We also grouped states by type of ELE program (e.g., ELE through income tax returns and ELE through SNAP), but found inconsistent results across model specifications (results not shown).

The results in table 6 suggest that ELE implementation had a sustained impact on Medicaid enrollment over the period of analysis. We explored this by including a continuous variable that measures the number of quarters since ELE was implemented in the state, along with an interaction term with the ELE dummy variable. We find that the interaction is positive and statistically significant at the 10 percent level in the Medicaid enrollment model only. This result hints that the ELE effect on enrollment could be stronger the longer states have had ELE in place. However, given the limited number of post-ELE implementation quarters, and the sensitivity of this result across model specifications, we will provide more confident estimates of the pattern of ELE effects over time in our subsequent analyses that are described below.

Discussion

In sum, our impact analysis finds significant evidence that ELE implementation increased Medicaid enrollment. Across a series of model specifications, estimated impacts of ELE were consistently positive, ranging between 4.0 and 7.3 percent, with most estimates statistically significant at the 5 percent level. Overall, these estimates had a central tendency of about 5.5

percent. The analyses also find suggestive evidence that ELE increased Medicaid/CHIP enrollment. Across a series of models, estimated impacts were again consistently positive, though less often statistically significant, with a central tendency of about 4.2 percent.

The less robust evidence of an effect of ELE on combined Medicaid/CHIP enrollment is not surprising given how modestly ELE has been implemented for ELE. Indeed, at the time of this analysis, only four states implemented ELE through CHIP, one of which (Iowa) had an ELE-like policy in effect prior to the period of analysis. We would also expect the effects from Oregon and Georgia's ELE programs would heavily weighted toward Medicaid, because each state's ELE agency, WIC and SNAP respectively, has income eligibility levels that encompass Medicaid threshold but which are below the CHIP threshold. In other words, these findings do not mean that ELE policies cannot affect CHIP enrollment, but rather that the existing ELE programs are more targeted towards Medicaid as opposed to CHIP enrollment.

While our results suggest that ELE can have a non-trivial effect on Medicaid enrollment, it's not guaranteed that the effect will be found in any particular state or in any particular type of ELE program. Our results suggest that ELE had an above average effect on enrollment in Iowa and Oregon, where ELE primarily functioned through SNAP, and in Maryland and New Jersey, where ELE functioned through the tax system as an outreach tool. However, measured effects of ELE must be seen in the context of a policy that can vary widely in both its implementation and its target population. An assessment of specific ELE features is challenging, as there is not enough statistical power to detect a difference between pre- and post-ELE enrollment for the many possible different ELE approaches. State policymakers that are considering ELE ought to expect that state-specific factors will influence the program's success, such as current Medicaid/CHIP participation rates, the number of applications and enrollments in an ELE partnership agency, the type of data that Medicaid or CHIP can pull from the other ELE agencies to determine eligibility, and other complementary policy changes that could enhance the effectiveness of ELE, such as application simplification and information technology and staffing upgrades.

Limitations

As with any quasi-experimental impact analysis, unobservable factors might bias our estimated ELE effects. Specifically, unless accounted for in our models, any factors correlated with the timing of ELE adoption that also affect enrollment might bias our estimates of ELE effects. For example, some states might have upgraded their information technology systems or implemented targeted outreach programs, subsequently increasing enrollment, at the same time they carried out ELE. For example, this may be an issue in New Jersey, where ELE was the centerpiece of a broader initiative to increase coverage of uninsured children eligible for Medicaid/CHIP and to ensure retention of enrollees in these programs (State of New Jersey 2009).[17] Thus inadequate controls for the adoption of other policy changes beyond those that we control for (e.g., observable changes to Medicaid/CHIP administrative simplification policies, the receipt of CHIPRA outreach dollars, and expansion of coverage to legal immigrants without

[17] For example, this initiative included broader changes to information technology, staffing, public awareness and media outreach, and application simplification.

a 5-year wait) will bias the estimated effect upward. In contrast, non-ELE states could be taking similar initiatives (unobservable to the researcher) that have a positive effect on Medicaid or CHIP enrollment, leading to a downward bias on the estimated ELE effect.

However, we have conducted a series of robustness checks that raise confidence in the magnitude and direction of the ELE effects found in the main modes. The estimates associated with the ELE variable only vary slightly across sensitivity tests and are not driven by the inclusion of a single variable (or set of variables) or the inclusion of a single ELE state, including New Jersey. We also find that the average ELE effect remains statistically significant and similar in magnitude to what we find in the main regression model when we exclude different sets of comparison states.

Our results also suggest that ELE may not result in a one-time increase in enrollment, but rather may have an effect that goes beyond initial implementation. However, this finding should be viewed with caution given the short post-ELE period available at the time of this analysis: most of the ELE policies were approved in 2010 or later and this analysis of the SEDS data was finalized in May 2012. Unlike other eligibility and enrollment simplification strategies that may diffuse slowly, ELE policies were quickly implemented and it’s possible that the effect could phase out over time. We rely on quarterly data to obtain the longest possible window of post-ELE data over the analysis period and will reassess impacts in 2013 when a longer post ELE experience will be available.

Finally, more research is needed to assess the effects of the non-ELE policy variables on Medicaid or Medicaid/CHIP enrollment. This analysis cannot conclude whether or not some of these policies had a positive or negative effect on enrollment during the period of analysis, as we did not subject the other policy variables to similar robustness analyses and there were very few changes in some of these policies (table 2) over the analysis period. In contrast, we are more confident in the ELE policy variable, given the certainty over the ELE implementation dates and the robustness of the estimated ELE effect based on the extensive range of sensitivity models that were estimated. A more rigorous analysis would be necessary to determine if the estimated effects of the other policy variables are sensitive to alternative model specifications.

Next Steps

In 2013, we will update the SEDS analysis and incorporate new findings into the report. By doing so, we can assess a much more substantial period of ELE performance in most states, enriching the statistical precision of the analysis and providing more detail on the effects of ELE, particularly those that might be lagged or time-limited. We will also use SEDS data on new Medicaid/CHIP enrollment to tease out ELE's effect on the flow of new enrollees, provided the data quality is sufficiently improved. This could provide additional information related to the effects of ELE on new Medicaid/CHIP enrollment as opposed to retention, as well as lead to additional policy recommendations. For instance, if the ELE effect from this study is primarily driven by new enrollment but not retention, it's possible that ELE's impact on enrollment will decrease over time if it associated with high levels of Medicaid/CHIP churning.

Appendix A: Changes in Medicaid/CHIP Policy from 2007 to 2011 among ELE and Non-ELE States

This appendix describes Medicaid/CHIP policy changes among ELE and non-ELE states during the period of analysis. For simplicity, the discussion of non-ELE states includes all 41 states as opposed to the subset comparison states in the Medicaid and Medicaid/CHIP models. Between 2007 and 2011, eligibility income thresholds for children's Medicaid/CHIP either increased or remained constant in every state. While two states, Missouri and Wisconsin, lowered the threshold for Medicaid eligibility during that time, the decreases were paired with equivalent increases in separate CHIP eligibility (in 2007 and 2011, respectively). Five of the eight ELE states (Alabama, Iowa, Oregon, Louisiana, and South Carolina) increased thresholds for children between 2007 and 2011, whereas only 13 of the 41 non-ELE states increased thresholds.

Eligibility income thresholds for parents also trended upward during that time, but not consistently. Of the eight states that modified parent thresholds, six increased them and two, Arizona in 2010 and Rhode Island in 2009, decreased them. Two ELE states, Maryland and New Jersey, increased eligibility thresholds for parents in 2008.

Several states added a separate CHIP program during this timeframe. At the start of 2007, 34 states, including six of the eight ELE states, had a separate CHIP program and by the last quarter of 2011, 37 states had CHIP program. Among the ELE states, Maryland removed its separate CHIP in 2007 (transferring those previously enrolled through CHIP to its Medicaid expansion program), Louisiana added a separate CHIP program in 2008, and South Carolina added a separate CHIP in 2008 but eliminated it in 2011. At the end of 2011, six ELE states still had a separate CHIP program. Many states with a separate CHIP enabled applicants to apply jointly for Medicaid and CHIP with one application form. In 2007, 32 of the 34 states with an SCHIP program had established this “no wrong door” policy, including all six ELE states with an SCHIP program. By 2011, 35 of the 37 CHIP states had a joint application, including all six ELE states with a separate program.

Fewer states have adopted presumptive eligibility policies, which enable entities such as schools, health-care providers, and community outreach organizations to make temporary Medicaid/CHIP eligibility determinations. In 2007, nine states and six states had presumptive eligibility for their Medicaid and SCHIP programs respectively, and 15 and 10 had such programs at the end of 2011. Among ELE states at the start of 2007, only New Jersey had presumptive eligibility in Medicaid or CHIP. Maryland added a separate CHIP program during the second quarter of 2007. Iowa added presumptive eligibility to both programs in 2010. Louisiana added it to their Medicaid program in 2007 and their CHIP program in 2008, only to remove it from both in 2009.

Between 2007 and 2011, there was a small increase in the use of administrative enrollment policies, whereby states can verify income through data matches with other government agencies. From the start of 2007 to the end of 2011, the number of states using this policy went from 9 to 13 in Medicaid and from 8 to 11 in CHIP. In 2007, the only ELE state to have this policy as part of its Medicaid program was Maryland; Alabama, Georgia, and

Maryland had it as part of their CHIP programs. By 2011 only Maryland's Medicaid program and Alabama's CHIP program used administrative enrollment among the ELE states.

The absence of required face-to-face interviews or asset tests was almost universal between 2007 and 2011. At the start of 2007, only Kentucky, Utah, New York, Tennessee and Mississippi required interviews in either a Medicaid or a separate CHIP program. Kentucky, Utah, and New York removed this requirement in 2008, 2009, and 2010, respectively, leaving Tennessee's Medicaid program and Mississippi's Medicaid and separate CHIP program as the only programs requiring an in-person interview in 2011. No ELE states did required interviews for either Medicaid or CHIP between 2007 and 2011.

At the start of 2007, only Texas, Utah, and two ELE states—Oregon and South Carolina—required asset tests in either their Medicaid programs or separate CHIP. Oregon removed the asset test requirement in their separate CHIP in 2010, while Missouri added an asset test in its separate CHIP in 2010. Only four states, Missouri, Texas, Utah, and South Carolina, required asset tests in either Medicaid or CHIP by the end of 2011. No state changed their Medicaid asset test requirement during the period of analysis, and as such this variable is excluded from the multivariate analysis.

Continuous coverage, where any enrolled child maintains coverage for 12 months from the time of enrollment, regardless of changing economic circumstances over that time, was used increasingly in Medicaid over 2007 and 2011, although it was more prevalent in separate CHIP. In 2007, 15 states, including four ELE states (South Carolina, Alabama, New Jersey, and

Louisiana), had continuous eligibility in Medicaid, and 23 states, including three ELE states (Alabama, New Jersey, and Iowa) had continuous eligibility in CHIP. Six states, including two ELE states (Iowa and Oregon) added continuous eligibility to their Medicaid programs prior to 2011 and no states removed it. In CHIP, only two states, including Oregon, added continuous eligibility to an existing separate CHIP. Three states, including South Carolina and Louisiana, included continuous eligibility in their new CHIPs. Arizona removed this policy from their separate CHIP. By 2011, 26 states, including five ELE states, had continuous eligibility in their separate CHIPs.

Appendix B: State-by-State Descriptive Analysis

In Alabama (figure B.1), Iowa (figure B.2 for Medicaid and figure B.3 for CHIP), and Maryland (figure B.4), enrollment steadily increases in the post-ELE period, but trends do not appear to change relative to the quarters immediately before ELE implementation. Similarly, in South Carolina, Medicaid enrollment declines slightly in the first of the two post-ELE implementation periods and subsequently increases (figure B.5). In contrast, Orzol et al. (2012) finds that Iowa's automatic Medicaid to S-CHIP referral program facilitated a sizeable number of new enrollments in Iowa's separate CHIP from 2009 to 2011. However, comparable data cannot be isolated in the SEDS data and it is not possible identify this effect in the multivariate analysis because the policy was in place prior to 2007.

Medicaid and CHIP enrollment in Oregon (figures B.6 and B.7) decrease by a few percent points in the first post-ELE implementation quarter, sharply increases in the subsequent quarter, and modestly grows in the remaining 2011 quarters. However, similar fluctuations in enrollment are observed in the state prior to ELE implementation.

In Georgia, total Medicaid enrollment decreased by approximately 1 percent and 8 percent respectively in the first and second quarters immediately after ELE was implemented, then increased by 10 percent in the last quarter of 2011 (figure B.8), while CHIP enrollment continued to decline following ELE implementation, consistent with the pre-ELE trend (figure B.9).

Figure B.10 shows that in Louisiana, Medicaid enrollment increased by around 1 percent in each of the first three quarters following ELE implementation, with smaller increases occurring over time; enrollment increased by 9,000 in Q2, compared to 7,300 and 6,500 in Q3 and Q4, respectively. Medicaid enrollment subsequently decreased by less than 1 percent in four out of the final five quarters in the period of analysis. These patterns appear consistent with the information available on Louisiana's ELE program as previously described. However, spikes in Medicaid enrollment do not show up in the SEDS because the data is aggregated into quarters, which could smooth out the one-time monthly increases seen in Orzol (2012).

From 2007 to 2011, New Jersey experienced its largest quarterly increase (6.7 percent, or 36,044 enrollees) in Medicaid enrollment in Q3 2009 (April–June 2009), the first quarter when ELE was in effect. Medicaid enrollment increased by more than 10,000 in the following two periods, with smaller increases occurring throughout the time period (figure B.11). This pattern—large increases in Medicaid enrollment in the first few quarters of ELE implementation followed by smaller sustained increases—is consistent with how the state's ELE program was implemented.[18] Similar to the Medicaid trend, CHIP enrollment in New Jersey increased during the first three months after ELE implementation. However, enrollment declined substantially in

[18] ELE applications for uninsured children who were potentially eligible for Medicaid or CHIP were sent beginning in May 2009 for all 2008 tax returns. For 2010 and 2011, applications were sent monthly, the bulk going out from January to May when people file their taxes.

Q2 2010, only to be reversed in Q4 2010 with modest changes in CHIP enrollment throughout 2011 (figure B.12). In contrast, Orzol et al. (2012) reports that fewer than 5,000 children became newly enrolled in Medicaid/CHIP through the ELE application in New Jersey. However, this data does not capture possible indirect effects from ELE. For instance, if a family in New Jersey received an ELE application in the mail, but subsequently applied for Medicaid/CHIP online or in-person, they would not be considered an ELE enrollee in the administrative data, whereas the SEDS impact analysis captures the total effect of ELE on Medicaid enrollment, regardless of how the application was processed.

Appendix C: Analysis of 2000-2011 Annual SEDS Data

This report also analyzed 2000 to 2011 annual SEDS data on total enrollment (the unduplicated number of children ever enrolled during the year) in the descriptive analysis to examine enrollment trends among ELE and non-ELE states before and after ELE implementation. As a sensitivity test, we also conduct a multivariate analysis using the annual 2006 to 2011 SEDS data from the same time period as the first congressionally mandated CHIP evaluation, during which several states changed their enrollment and renewal processes.

Figures C.1a and C.1b display the 2000 to 2011 annual SEDS data and highlights how Medicaid/CHIP enrollment in the 2007 to 2011 annual data are consistent with the trends in the 2007 to 2011 quarterly data. The annual enrollment numbers are consistently higher than the quarterly estimates within a given year. This difference emerges because the annual data measures enrollment at any point in the year as opposed to any point in the quarter. The appendix figure also shows how annual enrollment estimates among ELE states prior to 2004 appear more volatile relative to the more recent data and that enrollment grew faster during the recession years than in the middle part of the decade. The volatile annual enrollment estimates among ELE states prior to 2004 can be attributed to actual trends in Medicaid enrollment (which could be influenced by policy changes prior to 2006 not documented in this report) or earlier SEDS data being more prone to reporting error, although these data were previously validated by CMS.

Table C.1 shows the full regression results from the 2006 to 2011 annual SEDS data, using the same group of comparison states and control variables that were used in the main models in the quarterly analysis. The direction and magnitude associated with the ELE variable is consistent across the annual and quarterly models (0.0299 versus 0.0420 in the total enrollment model and 0.0471 versus 0.0562 in the Medicaid-only model) but the ELE variable in the annual models is not statistically significant at conventional levels (the p-values are .386 in the Medicaid/CHIP model and .125 in the Medicaid model). This is not surprising, considering that there are few post-ELE implementation years and that the annual data are less precise. The annual model also treats implementation years as post-ELE periods, which introduces additional measurement error relative to the main quarterly model.

Appendix D: Sensitivity Analysis Results

As mentioned in the main text, the results from alternatives 1 and 3 show that the inclusion or exclusion of policy variables in the main model—which uses the designated sets of comparison states described in the methods— has a small impact on the magnitude of the ELE variable, but has a more substantial effect on the level of statistical significance. In addition, removing the unemployment rate and child population (alternative 2) from the main model has a negligible effect on the ELE results.

Appendix Table D.1 further explores the policy variables by analyzing the effect of going from alternative 3 (the simple unadjusted difference-in-difference model with state and quarter fixed effects and demographic controls), to adding each of the policy covariates one at a time, and the effect of subtracting one policy at a time from the full model. The ELE coefficient in the Medicaid model remains statistically significant at the 10 or 5 percent level in each model where a policy variable is subtracted one at a time. Removing the simulated parent eligibility variable lowers the magnitude associated with the ELE coefficient by about 1.4 percentage points from 5.6 to 4.2, but does not alter the statistical significance. Removing joint application and administrative verification of income has a small negative effect on the ELE variable's statistical significance (p-value increases from around .03 to just over .05), but does not have much of an effect on the magnitude. The next column under the Medicaid enrollment model shows that adding the parent eligibility variable, presumptive eligibility, and administrative verification of income one at a time adds some statistical significance on the ELE variable in the basic unadjusted model (p-values range from .07 to .09). In contrast, the p-values associated with the ELE variable in the models that add the other variables in this column are just over .1.

In contrast, the first two columns of Table D.1 show that the level of statistical significance in the Medicaid/CHIP model is more sensitive to the exclusion or inclusion of specific policy controls. The ELE effect becomes statistically insignificant, with p-values just above .1, when the following variables are removed one at a time from the fully adjusted model: parent eligibility, presumptive eligibility (Medicaid), no in-person interview (Medicaid), and administrative verification of income (CHIP). The ELE effect in the unadjusted model remains statistically insignificant when you add each policy variable one at a time. However, the direction and magnitude is relatively stable across all of these models.

These results provide reassurance that the magnitude of the ELE effect is not driven by other observed policy or economic changes correlated with ELE implementation or with policy choices among non-ELE states. Our results show that the ELE variable remains positive and similar in magnitude even when we do not control for the other policy changes and when the policy variables are removed from the main model one at a time. We also find that the coefficient on the ELE variable remains statistically significant and relatively constant in magnitude after controlling for recent (2009 onward) child immigrant expansions and level of outreach grants states received under CHIPRA (results not shown).

The results from alternatives 1 through 4 also provide confidence that the main results are not driven by measurement error or multicollinearity. While we are extremely confident in the accuracy of the ELE implementation dates, there is some uncertainty over the accuracy of the dates for the other policy variables, especially for changes that occurred earlier in the period of analysis. As an additional test, we find that the ELE effect remains positive and statistically significant even when we lag all of the time-varying covariates by one or two fiscal quarters (results not show). The finding that the ELE effect remains when the policy variable dummies are aggregated into a single index (alternative 4) suggests that multicollinearity is not distorting the overall ELE effect. The main regression models suffer from high levels of multicollinearity, as measured by the variance inflation factor (VIF). However, we find that the VIF is in a normal range when we remove the time-varying covariates from the main model, while the ELE coefficient changes very little.

The results from alternative models 6 through 11 further validate the ELE effect found in the main Medicaid model by showing that the ELE effect persists even after using various groupings of non-ELE comparison states, while casting some doubt on the robustness of the Medicaid/CHIP model. In alternative 6, we increase the significance threshold to 10 percent for rejecting the null of no difference in pre-ELE enrolment trend differences, thereby dropping 3 additional states in both models. In alternative 7, we decrease the significance threshold to 1 percent and include 10 additional comparison states in the Medicaid/CHIP model and 3 additional states in the Medicaid models. Using the alternative procedure based on quarter-quarter trend differences (alternative 8), we only include 15 comparison states in the Medicaid/CHIP model and 19 comparison states in the Medicaid model. Under these three alternatives, the ELE effect remains relatively unchanged in the Medicaid model, whereas the

ELE coefficient is less than one percentage point smaller and no longer statistically significant in the Medicaid/CHIP model (the p-value ranges from .12 for alternatives 6 and 7 to .37 for alternative 8).

The composition of the comparison groups differ across the Medicaid/CHIP and Medicaid models because more non-ELE states have significantly different CHIP enrollment trends compared to the ELE state average prior to 2009. However, when we use the same comparison states in the Medicaid/CHIP model that were selected in the Medicaid model, we find that the ELE effect is positive (in the neighborhood of 4.5 percent) and statistically significant across all specifications of the comparison group exclusion tests.

In alternative 9, we remove outlier states that might not serve as the most appropriate comparison for ELE states and find that the ELE effect is even stronger relative to the main model results. For alternatives 10 and 11, we re-estimated the simple Medicaid/CHIP and Medicaid only models, including one non-ELE state at time to determine which control states have the strongest influence on the ELE coefficient. We then rank the states based on the estimated ELE coefficient when they are included in the model. For the Medicaid/CHIP and Medicaid only models under alternative 10, we remove the top and bottom 5 states based on this ranking. We find that removing these 10 states resulted in a stronger ELE effect in the Medicaid only model and a slightly lower but still statistically significant effect in the total Medicaid/CHIP model. We also find that the ELE effect remains statistically significant and comparable in magnitude in the Medicaid only model even after we remove the top and bottom 10 states in the distribution (alternative 11).

Alternatives 12 through 14 show that the Medicaid model results are insensitive to specifying alternative ELE implementation dates. Using an alternative implementation date for Louisiana and Alabama, where ELE was implemented in stages, has no effect on the ELE coefficient in both the Medicaid and Medicaid/CHIP models. However, using Q3 2010 instead of Q1 2009 as the implementation date in Maryland results in a slightly lower ELE effect (less than one percentage point) in both the Medicaid and combined Medicaid/CHIP models. The coefficient associated with the ELE variable remains statistically significant at the 5 percent level in the Medicaid model, but is no longer statistically significant in the Medicaid/CHIP model (p-value=.124).

We also estimated several alternative models where the results (not shown) were nearly identical to the results from the main model specification. Including the size of the adult population and state-quarter personal income as additional time-varying controls resulted in a slightly higher ELE effect, but this model suffers from higher levels of multicollinearity relative to the main model. The ELE coefficient is also insensitive to removing the log transformation on the child population and using the non-simulated versions of the Medicaid/CHIP eligibility variables. Replacing the quarter fixed effects with year fixed effects increases the magnitude on the ELE coefficient and using a time trend variable instead of the quarter fixed effects further increases the ELE effect. This suggests that models that do not include quarter fixed effects create an upward bias on the ELE coefficient. We also find that the ELE effect was even stronger when we weighted the regression model by the state's nonelderly population.

In alternative models where dependent variables was not log transformed, we found that the ELE coefficient was negative and statistically insignificant in the Medicaid model and positive in the Medicaid/CHIP model. However, analysis of the untransformed dependent variables, through residual plots and Shapiro-Wilk tests of normality (results not shown), show that Medicaid and CHIP enrollment and their associated regression residuals are not normally distributed, violating a major assumption of the linear regression model and raising concerns about the validity of this model specification. When we define the dependent variables as the proportion of the state's child population enrolled in Medicaid/CHIP or Medicaid, the ELE coefficient remains positive and significant in the Medicaid model.

Finally, it is important to note that to be conservative, we report cluster-robust standard errors, which is a more robust covariance matrix estimator relative to other methods that correct for autocorrelation (e.g., Newey-West). Not surprisingly, we find that the Newey-West standard errors are smaller than the cluster-robust standard errors and therefor yield more statistically significant effects. For example, under the Newey-West scenario, the ELE effect is statistically significant at the 10 percent level in the Medicaid/CHIP model and at the 5 percent level in the Medicaid only model under alternative 5, where all non-ELE states are included in the comparison group (the coefficients are unchanged).

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Table 1. States with Approved State Plan Amendments for CHIPRA Express Lane Eligibility as of January 2012

State	Health Program	Eligibility Factors	Express Lane Program(s)	ELE Function	Implementation Date	SEDS Implementation Date (Fiscal Year)	# of Post-ELE Quarters
Alabama I	Medicaid	Income	SNAP; TANF	Renewal	10/1/2009	Q1 2010	8
Alabama II	Medicaid	Income	SNAP; TANF	Initial determination and renewal	4/1/2010	Q3 2010	6
Georgia	Medicaid & CHIP	Income, identity, age, state residence	WIC	Initial determination	1/1/2011	Q2 2011	3
Iowa	Medicaid & CHIP	except immigration status and citizenship from SNAP; Income for Medicaid & CHIP	SNAP; Medicaid[a]	Initial determination (SNAP); redetermination (Medicaid)	6/1/2010 (SNAP); 7/1/2010 (Medicaid)	Q4 2010	5
Louisiana I	Medicaid	Income, state residence, SSN, identity	SNAP	Initial determination and renewal	2/10 for applications; 10/10 for renewals	Q2 2010	7
Louisiana II	Medicaid	Income, state residence, SSN, identity	SNAP	Initial determination and renewal	12/09 for applications; 10/10 renewals	Q1 2010	8
Oregon	Medicaid & CHIP	Income and state residence (and SSN, for SNAP)	SNAP; NSLP (pilot)	Initial determination	8/1/2010 for SNAP[b]; 11/11 for NSLP	Q4 2010	5
South Carolina	Medicaid	Income and assets	SNAP; TANF	Renewal	4/1/2011	Q3 2011	2
New Jersey	Medicaid & CHIP	Income and identity	State income tax; NSLP (pilot)	Initial determination and renewal[c]	5/1/2009	Q3 2009	10
Maryland I	Medicaid	State residence	State income tax	Initial determination	5/1/2008 (tax-based outreach)	Q1 2009[d]	12
Maryland II	Medicaid	State residence	State income tax	Initial determination	4/1/2010 (tax-based ELE)	Q3 2010	6

Source: Urban Institute analysis of CHIP and Medicaid State Plan Amendments, Centers for Medicare and Medicaid Services.

Notes: (1) For states with two rows, the first row corresponds to the implementation date used for the main analysis and the second row corresponds to the sensitivity analysis date. (2) Federal fiscal year quarters are as follows: first quarter, October 1 through December 31; second quarter, January 1 through March 31; third quarter, April 1 through June 30; and fourth quarter, July 1 to September 30.

a: This program uses one-way Medicaid-to-CHIP ELE referrals. There are no CHIP-to-Medicaid ELE referrals. ELE is used for redeterminations that result in a child being transferred from Medicaid to CHIP.

b: The SNAP initiative was effective statewide in September 2010, but approved by CMS in August.

c: New Jeresey's ELE program is authorized for applications and renewals, but officials claim ELE has only been used for initial applications at this point.

d: Maryland's tax-based outreach program was implemented in May 2008, but applications were not sent out until September.

Table 2. Number of States with Medicaid/CHIP Administrative Simplification Policies and Average Eligibility Thresholds by Year ELE vs. Non-ELE States

	2007		2008		2009		2010		2011	
	ELE	Non-ELE	ELE	Non-ELE	ELE	Non-ELE	ELE	Non-ELE	ELE	Non-ELE
Medicaid Program	**8**	**41**	**8**	**41**	**8**	**41**	**8**	**41**	**8**	**41**
Presumptive eligibility, Medicaid	1	8	2	12	2	12	1	12	2	13
Administrative verification of Income, Medicaid	1	8	1	9	2	9	2	12	1	12
No in-person interview, Medicaid	8	36	8	36	8	38	8	38	8	39
Continuous eligibility, Medicaid	4	11	4	11	6	12	6	14	6	15
Average Child Medicaid Income Eligibility Threshold (% FPL)	145	161	157	161	157	164	158	164	164	161
Average Parent Medicaid Income Eligibility Threshold (% FPL)	66	91	70	91	87	92	78	88	78	91
Separate CHIP	**6**	**28**	**5**	**30**	**7**	**30**	**7**	**30**	**6**	**31**
Medicaid/CHIP Joint Application	6	26	5	27	6	28	6	28	6	29
Presumptive eligibility, CHIP	1	5	1	8	2	7	1	7	2	8
Administrative verification of Income, CHIP	3	5	1	6	2	6	2	9	1	10
No in-person interview, CHIP	6	25	5	27	7	29	7	29	6	30
No asset test, CHIP	5	27	4	29	5	29	6	29	6	29
Continuous eligibility, CHIP	3	20	3	22	6	22	6	22	5	21
Average CHIP Income Eligibility Threshold (% FPL)	245	218	234	225	231	232	276	235	289	241

Source: 2007 to 2012 publications from the Kaiser Commission on Medicaid and the Uninsured and the Georgetown Center for Children and Families.

Notes: (1) Policies in place during first fiscal quarter, except in 2011. In 2011, policies in place during the fourth fiscal quarter are shown. (2) ELE states are Alabama, Georgia, Iowa, Louisiana, Maryland, New Jersey, Oregon, and South Carolina. Non-ELE states include all other states except Maine and Montana. (3) CHIP thresholds are estimated among states with separate CHIP programs. (4) Medicaid counts includes Title XIX or TItle XXI Medicaid.

Figure 1a.
Average Medicaid Enrollment Among ELE States and Comparison States , 2007-2011

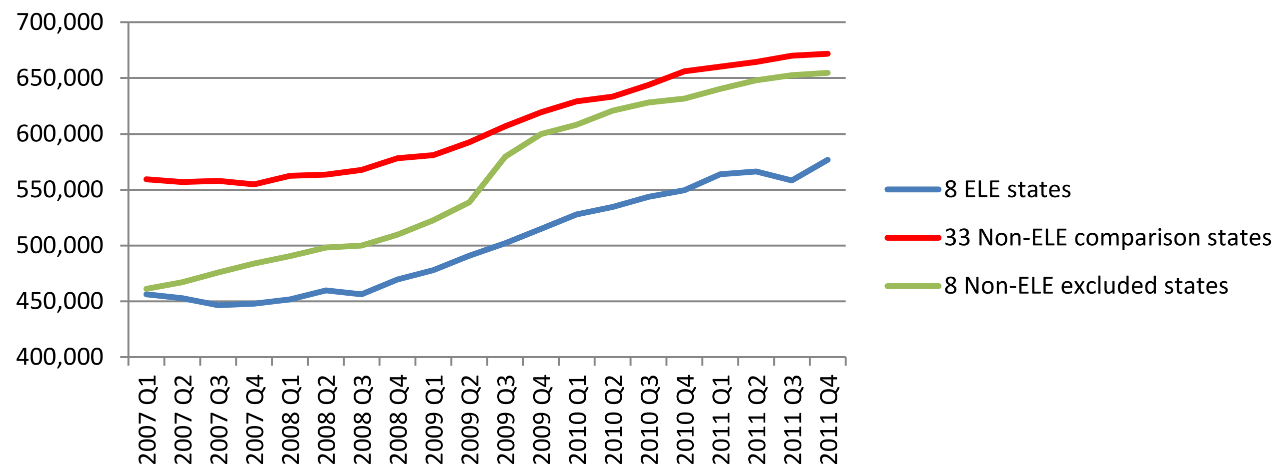
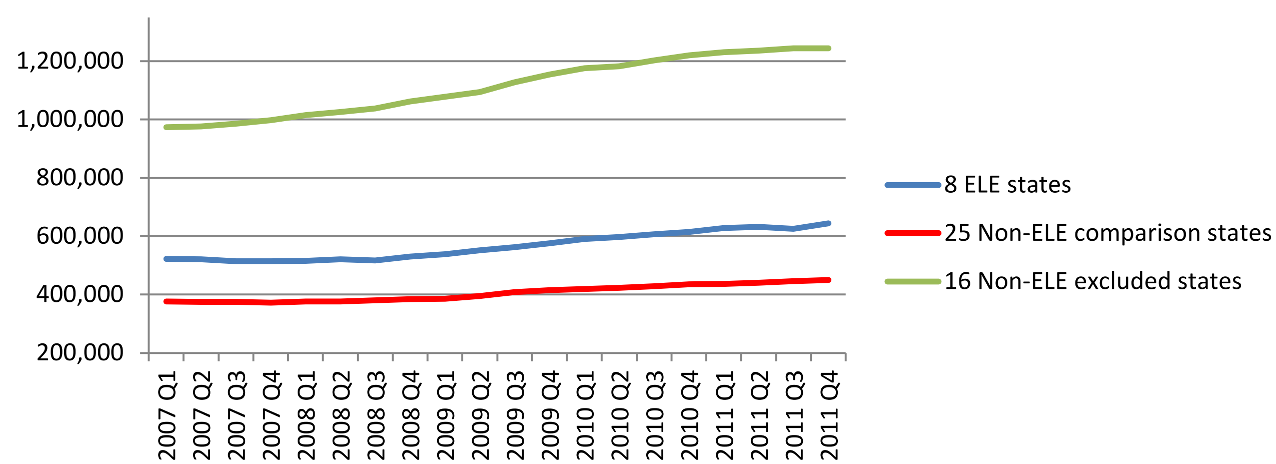


Figure 1b.
Average Medicaid/CHIP Enrollment Among ELE States and Comparison States , 2007-2011



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. (2) ELE states in Alabama, Georgia, Iowa, Louisiana, Maryland, New Jersey, Oregon, and South Carolina. Maine and Montana are excluded from all samples.

Table 3. Results for Main Multivariate Regression Models
2007-2011 Quarterly SEDS Data

	Dependent Variable (log transformed)	
	Total Medicaid/CHIP Enrollment	**Medicaid Enrollment Only**
Express Lane Eligibility	0.0420*	0.0562**
	(0.024)	(0.026)
Unemployment Rate	0.0067	0.0055
	(0.006)	(0.006)
Log(Child Population)	0.8550**	1.209***
	(0.381)	(0.414)
Separate CHIP	0.0120	-0.0104
	(0.023)	(0.017)
Simulated Eligibility Threshold for Children	0.0003	0.0005
	(0.001)	(0.001)
Simulated Eligibility Threshold for Parents	-0.0024	-0.0037
	(0.002)	(0.002)
Joint Application	-0.0331	-0.0279
	(0.027)	(0.027)
Presumptive Eligibility-Medicaid	0.0589	0.0192
	(0.042)	(0.026)
Admin. Verification of Income-Medicaid	0.0222	0.0635***
	(0.050)	(0.023)
No In-Person Interviews-Medicaid	0.0390	0.0254
	(0.061)	(0.042)
Continuous Eligibility-Medicaid	0.0443	0.0375
	(0.049)	(0.028)
Presumptive Eligibility-CHIP	-0.0153	N/A
	(0.044)	
Admin. Verification of Income-CHIP	-0.0108	N/A
	(0.053)	
No In-Person Interviews-CHIP	0.0281	N/A
	(0.052)	
No Asset Test-CHIP	0.0273	N/A
	(0.061)	
Continuous Eligibility-CHIP	0.0120	N/A
	(0.051)	
Constant	1.005	-3.995
	(5.295)	(5.776)
R-sqr	0.99	0.99
Sample size	660	820

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and quarter fixed effects (coefficients not shown) (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Table 4. Estimated ELE Effects for Alternative Models
2007-2011 Quarterly SEDS Data

	Dependent Variable (log transformed)	
	Total Medicaid/CHIP Enrollment	**Medicaid Enrollment Only**
Main Regression Model	0.0420*	0.0562**
	(0.024)	(0.026)
Alternative specification of control variables		
(1) State and quarter fixed effects only (unadjusted model)	0.0349	0.0406
	(0.028)	(0.025)
(2) Unadjusted model+policy variables	0.0471*	0.0587**
	(0.024)	(0.026)
(3) Unadjusted model +unemployment rate and child population	0.0346	0.0401
	(0.028)	(0.025)
(4) Policy index instead of dummy variables	0.0478*	0.0518**
	(0.0280)	(0.025)
Alternative specification of comparsion states		
(5) Include all 41 non-ELE states as comparison states	0.0335	0.0422
	(0.022)	(0.026)
(6) 10% significance threshold for dropping comparison state	0.0360	0.0595**
	(0.022)	(0.026)
(7) 1% significance threshold for dropping comparison state	0.0377	0.0565**
	(0.024)	(0.025)
(8) Excluding states based on joint test	0.0244	0.0551*
	(0.026)	(0.029)
(9) Excluding outlier comparison states	0.0425**	0.0726***
	(0.020)	(0.023)
(10) Excluding top 5 and bottom 5 comparison states in terms of ELE effect	0.0364*	0.0552**
	(0.020)	(0.024)
(11) Excluding top 10 and bottom 10 comparison states in terms of ELE effect	0.0277	0.0506*
	(0.018)	(0.025)
Alternative specification of ELE implementation dates		
(12) Alternative implementation date: Alabama	0.0438*	0.0580**
	(0.024)	(0.026)
(13) Alternative implementation date: Maryland	0.0328	0.0495**
	(0.021)	(0.024)
(14) Alternative implementation date: Louisiana	0.0417*	0.0545**
	(0.024)	(0.026)

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and quarter fixed effects (coefficients not shown). All other right hand side variables are the same as those in the table 3 main results. (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Table 5. Estimated ELE Effect for Models on Different Subsets of ELE States
2007-2011 Quarterly SEDS Data

	Dependent Variable (log transformed)	
	Total Medicaid/CHIP Enrollment	**Medicaid Enrollment Only**
Main Regression Model	0.0420*	0.0562**
	(0.024)	(0.026)
Models Excluding Individual States		
Alabama	0.0509*	0.0625**
	(0.028)	(0.030)
Georgia	0.0527**	0.0642**
	(0.024)	(0.027)
Iowa	0.0295	0.0480*
	(0.024)	(0.028)
Louisiana	0.0554**	0.0739***
	(0.026)	(0.024)
Maryland	0.0325	0.0515*
	(0.024)	(0.026)
New Jersey	0.0382	0.0514*
	(0.026)	(0.027)
Oregon	0.0390	0.0344
	(0.024)	(0.022)
South Carolina	0.0494*	0.0636**
	(0.026)	(0.026)

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and quarter fixed effects (coefficients not shown). All other right hand side variables are the same as those in the table 3 main results. (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter. (5) The Medicaid/CHIP models include 660 and the Medicaid model includes 820 state-quarter observations.

Table 6. Estimated ELE Effect for Regressions that Model the ELE Effect over Time
2007-2011 Quarterly SEDS Data

	Dependent Variable (log transformed)	
	Total Medicaid/CHIP Enrollment	**Medicaid Enrollment Only**
Main Regression Model	0.0420*	0.0562**
	(0.024)	(0.026)
Number of quarters since ELE implementation		
ELE	0.0279	0.0374
	(0.024)	(0.024)
ELE*Number of quarters since ELE implementation	0.00401	0.00509*
	(0.003)	(0.003)

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and quarter fixed effects (coefficients not shown). All other right hand side variables are the same as those in the table 3 main results. (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter. (5) The Medicaid/CHIP models include 660 and the Medicaid model includes 820 state-quarter observations.

Table S.1. Trends in Medicaid and CHIP Enrollment Among ELE States
2007-2011 Quarterly SEDS Enrollment

		Alabama		Georgia		Iowa		Louisiana		Maryland		New Jersey		Oregon		South Carolina	
Year	Fiscal Quarter	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP	Medicaid	CHIP
2007	Q1	415,365	73,279	795,998	300,361	193,627	20,147	684,290	N/A	411,498	13,154	502,388	84,486	210,385	39,306	435,924	N/A
	Q2	445,496	74,028	778,842	305,543	193,458	23,818	654,435	N/A	405,412	14,032	505,305	85,349	206,272	42,729	432,026	N/A
	Q3	410,315	74,636	766,860	293,950	195,454	22,929	653,464	1,007	405,019	N/A	506,695	86,368	207,011	45,819	425,657	N/A
	Q4	406,007	77,017	746,212	296,789	197,677	23,979	664,038	1,681	421,591	N/A	518,131	84,536	206,914	47,071	421,542	N/A
2008	Q1	408,910	77,336	768,798	287,188	198,910	23,830	668,018	1,831	**428,742**	N/A	511,346	76,221	201,705	48,209	426,195	N/A
	Q2	410,629	78,786	811,349	262,657	199,748	23,670	675,222	1,961	440,742	N/A	513,078	76,348	207,752	49,813	432,470	N/A
	Q3	377,328	78,825	789,035	249,180	202,815	24,157	679,026	2,206	434,206	N/A	520,369	77,837	213,527	51,876	434,878	2,048
	Q4	400,104	79,909	830,734	238,469	207,137	23,490	687,150	3,571	437,971	N/A	526,339	78,940	216,740	52,509	448,738	5,779
2009	Q1	**416,215**	79,017	847,744	229,499	214,778	22,939	690,591	4,196	447,788	N/A	531,616	79,263	221,583	55,044	451,701	9,286
	Q2	432,325	78,358	867,210	225,703	220,602	22,544	697,224	4,494	**454,580**	N/A	540,700	79,643	237,484	58,954	458,260	12,078
	Q3	440,129	76,959	886,505	225,921	227,470	23,552	703,050	4,883	461,224	N/A	576,744	83,874	256,255	56,086	464,802	14,944
	Q4	450,346	77,320	904,278	220,884	253,877	25,516	714,674	5,504	475,584	N/A	587,883	87,812	252,962	50,900	480,170	16,196
2010	Q1	460,127	83,270	930,800	223,020	256,707	27,392	726,581	5,567	**481,651**	N/A	603,131	90,680	277,529	57,981	486,792	16,946
	Q2	**470,262**	84,659	925,626	225,482	261,969	29,594	735,413	5,513	487,604	N/A	612,515	76,337	290,688	61,217	491,284	16,832
	Q3	480,396	85,918	944,438	222,570	266,722	32,614	742,666	5,756	**497,440**	N/A	621,941	78,001	297,234	65,869	497,079	17,401
	Q4	492,001	81,880	951,748	217,224	270,934	34,318	749,170	5,966	508,743	N/A	630,845	96,154	288,775	64,634	504,903	17,862
2011	Q1	499,069	80,945	998,573	217,940	272,312	36,615	748,284	5,933	515,244	N/A	639,755	98,300	312,517	75,283	524,395	N/A
	Q2	505,911	82,846	989,334	215,607	274,665	38,780	743,877	6,017	522,863	N/A	645,531	99,533	320,783	78,493	527,402	N/A
	Q3	507,888	86,354	909,930	218,471	276,872	39,909	741,076	6,210	531,628	N/A	653,144	101,191	326,705	80,950	519,413	N/A
	Q4	521,664	88,589	1,004,598	217,157	281,189	40,607	746,196	6,336	537,051	N/A	661,540	101,055	332,096	84,023	529,382	N/A

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter. CHIP enrollment only includes children who were ever enrolled in a separate CHIP during the fiscal quarter.(3) Values in bold were imputed by the Urban Institute using methods described in the paper. (3) N/A indicates that the state did not have a separate CHIP during the quarter.

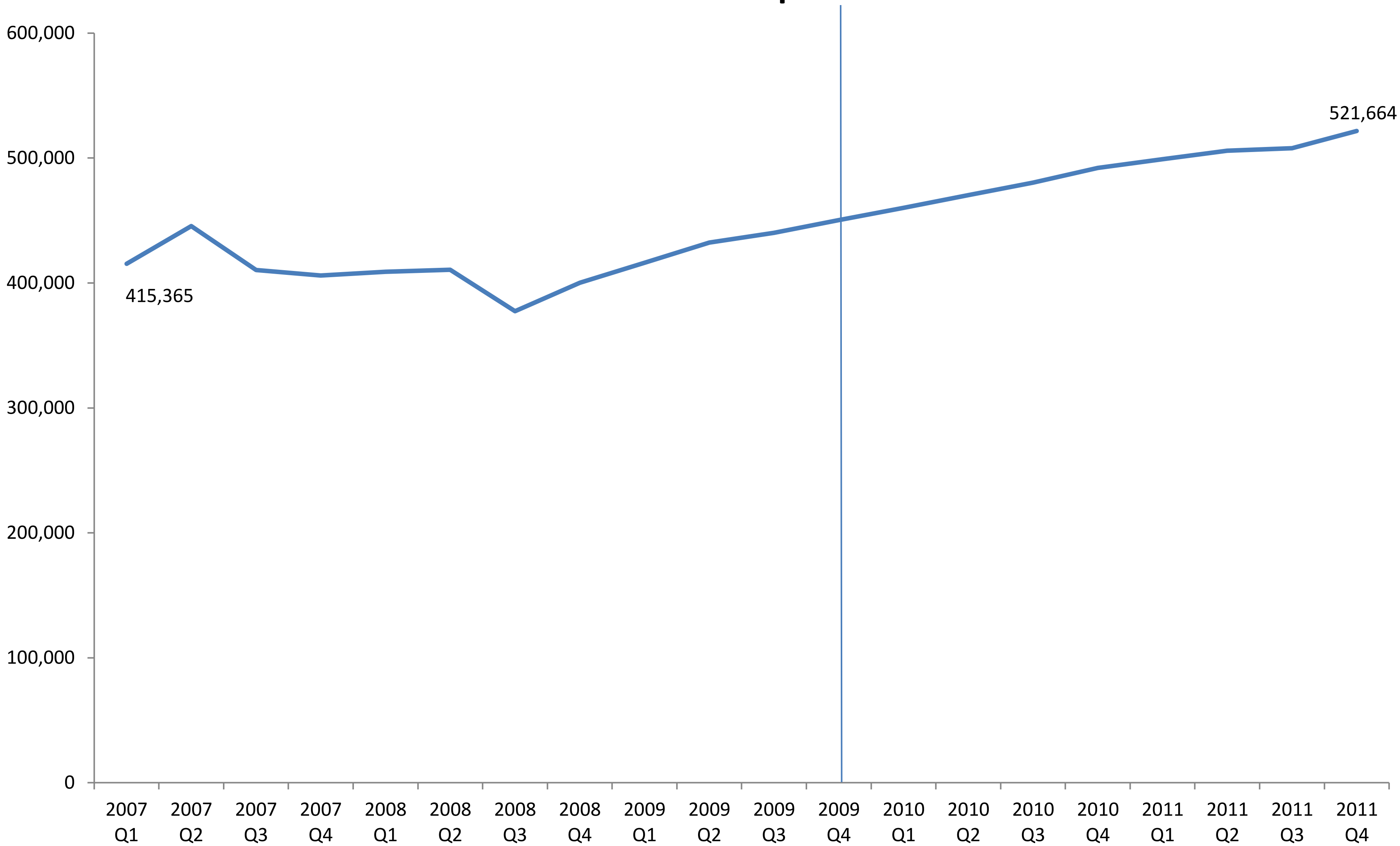
Table S.2. Trends in Medicaid and CHIP Enrollment Among ELE States
2000 to 2010 Annual SEDS Enrollment

	Alabama		Georgia		Iowa		Louisiana		Maryland		New Jersey		Oregon		South Carolina	
	Medicaid	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**	**Medicaid**	**CHIP**
Year																
2000	338,952	37,587	1,058,910	120,626	161,597	8,699	583,501	0	376,198	0	484,409	50,361	245,270	37,092	441,781	0
2001	373,536	49,008	740,423	182,762	170,628	16,672	560,114	0	399,535	308	487,122	58,721	255,765	41,468	517,591	0
2002	413,363	66,027	1,491,037	221,005	190,424	21,133	610,080	0	427,587	3,875	506,988	75,036	268,590	42,976	540,130	0
2003	438,354	78,554	900,517	251,711	203,084	23,059	688,666	0	445,973	7,932	490,513	78,858	270,731	44,752	597,227	0
2004	447,363	79,407	1,023,632	280,083	217,167	26,640	699,278	0	457,163	9,824	502,140	87,374	271,675	46,720	554,722	0
2005	457,460	81,856	1,082,007	306,733	227,543	30,109	789,407	0	461,586	13,845	519,841	86,156	277,372	52,722	568,688	0
2006	487,567	84,257	1,144,432	343,690	237,443	31,819	792,560	0	467,370	23,911	551,837	92,811	278,283	59,039	568,555	0
2007	486,930	106,691	952,973	356,285	242,251	32,312	790,951	1,877	475,784	12,530	550,582	100,991	268,612	63,090	549,755	0
2008	477,466	110,821	970,860	311,243	248,002	32,681	775,902	5,319	493,969	0	581,251	95,153	270,320	73,686	545,375	5,821
2009	519,672	110,158	1,047,790	254,365	291,323	34,316	798,091	8,431	526,034	0	641,888	102,674	**324,413**	**81,256**	575,123	18,297
2010	**567,216**	**100,530**	1,098,937	248,268	312,244	44,844	810,393	9,480	556,784	0	693,090	112,016	**352,718**	**93,366**	538,299	20,461
2011	**599,677**	**109,255**	1,168,338	248,536	327,177	54,114	814,209	9,846	585,315	0	720,150	117,897	385,131	112,069	573,109	0

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

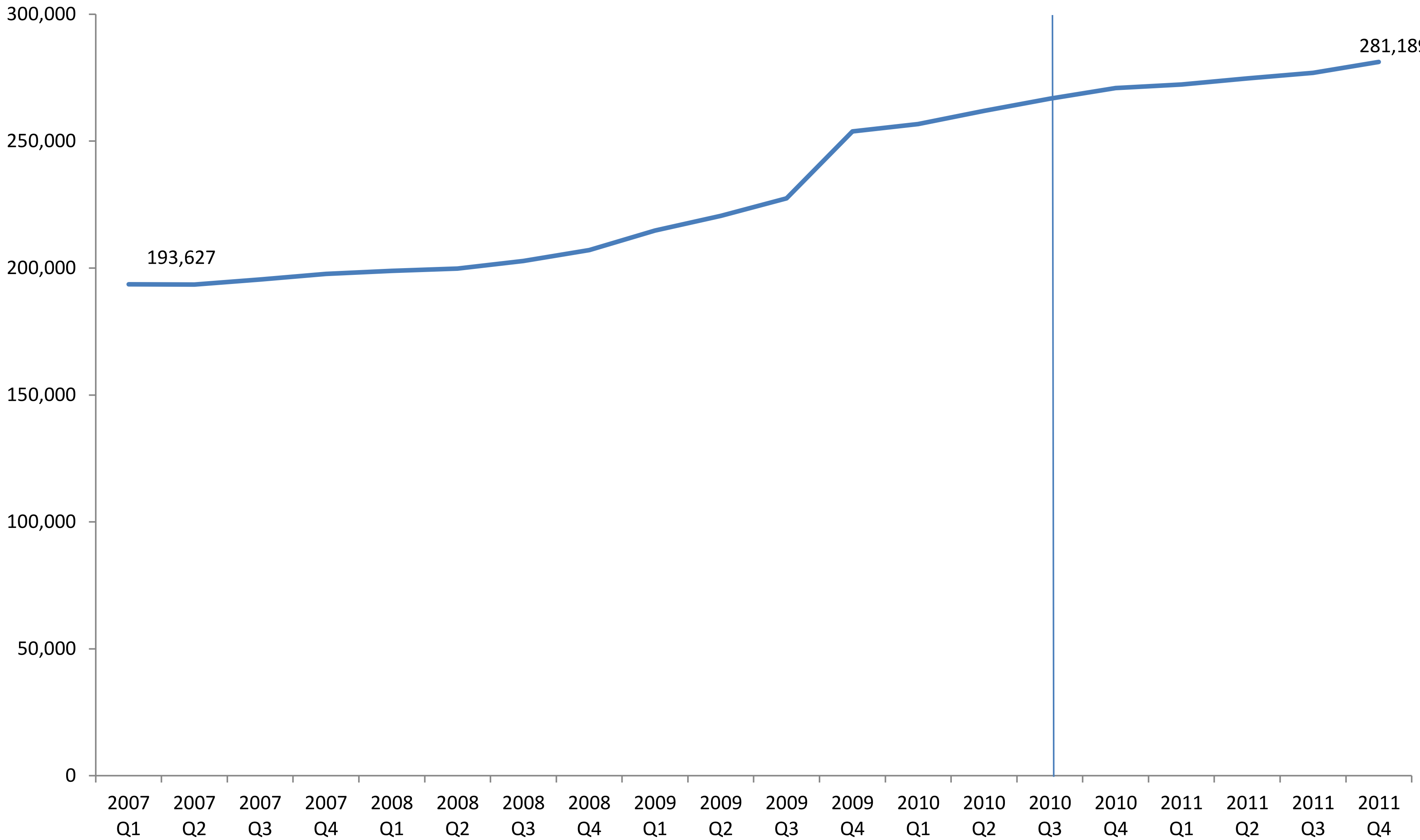
Notes: (1) Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal year. CHIP enrollment only includes children who were ever enrolled in a separate CHIP during the fiscal year. (2) Values in bold were imputed by the Urban Institute using methods described in the paper. (3) N/A indicates that the state did not have a separate CHIP during the year.

Figure B.1. Medicaid Enrollment in Alabama before and after ELE Implementation

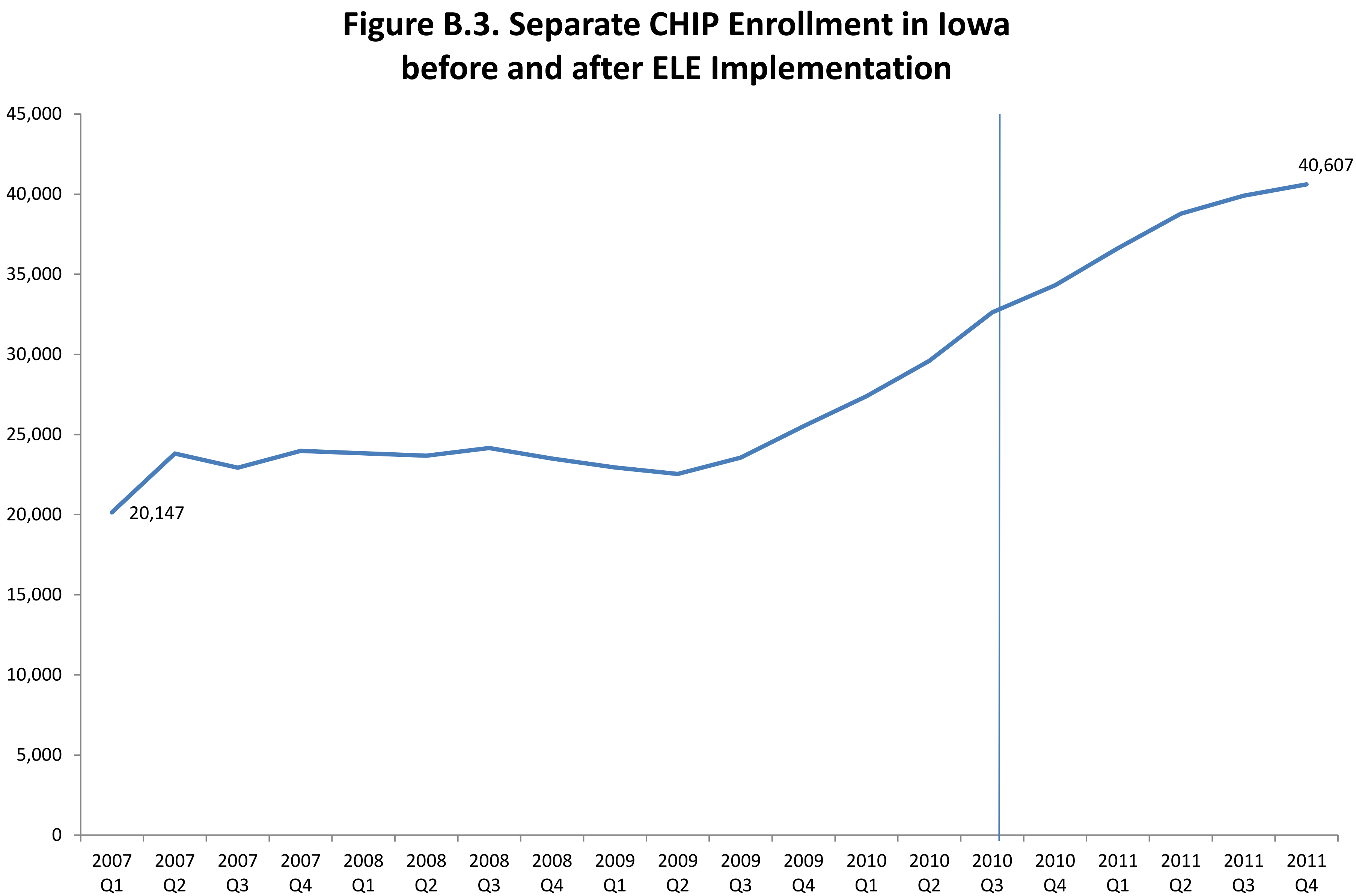


Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Figure B.2. Medicaid Enrollment in Iowa before and after ELE Implementation

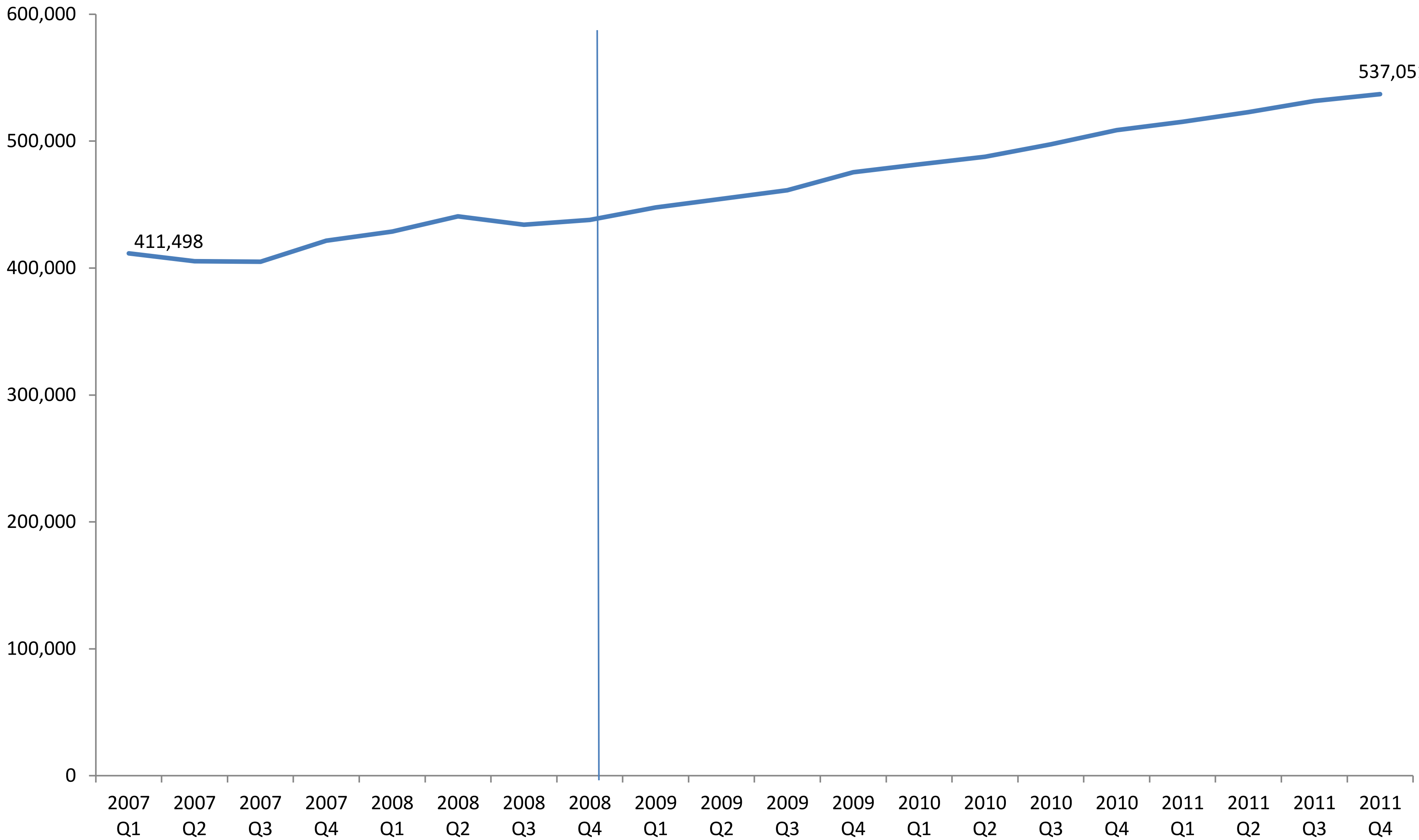


Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.



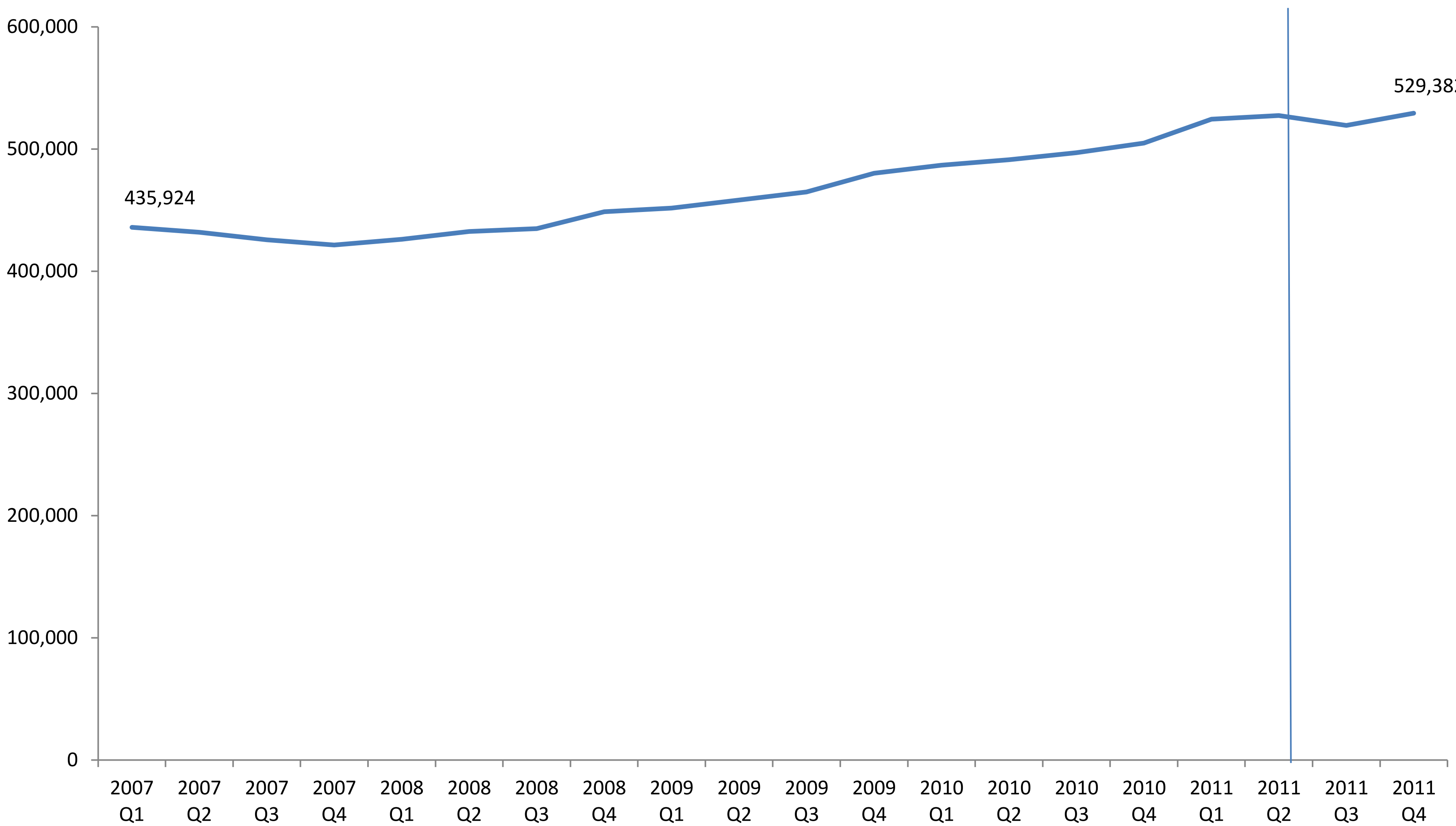
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in CHIP during the fiscal quarter.

Figure B.4. Medicaid Enrollment in Maryland before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Figure B.5. Medicaid Enrollment in South Carolina before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

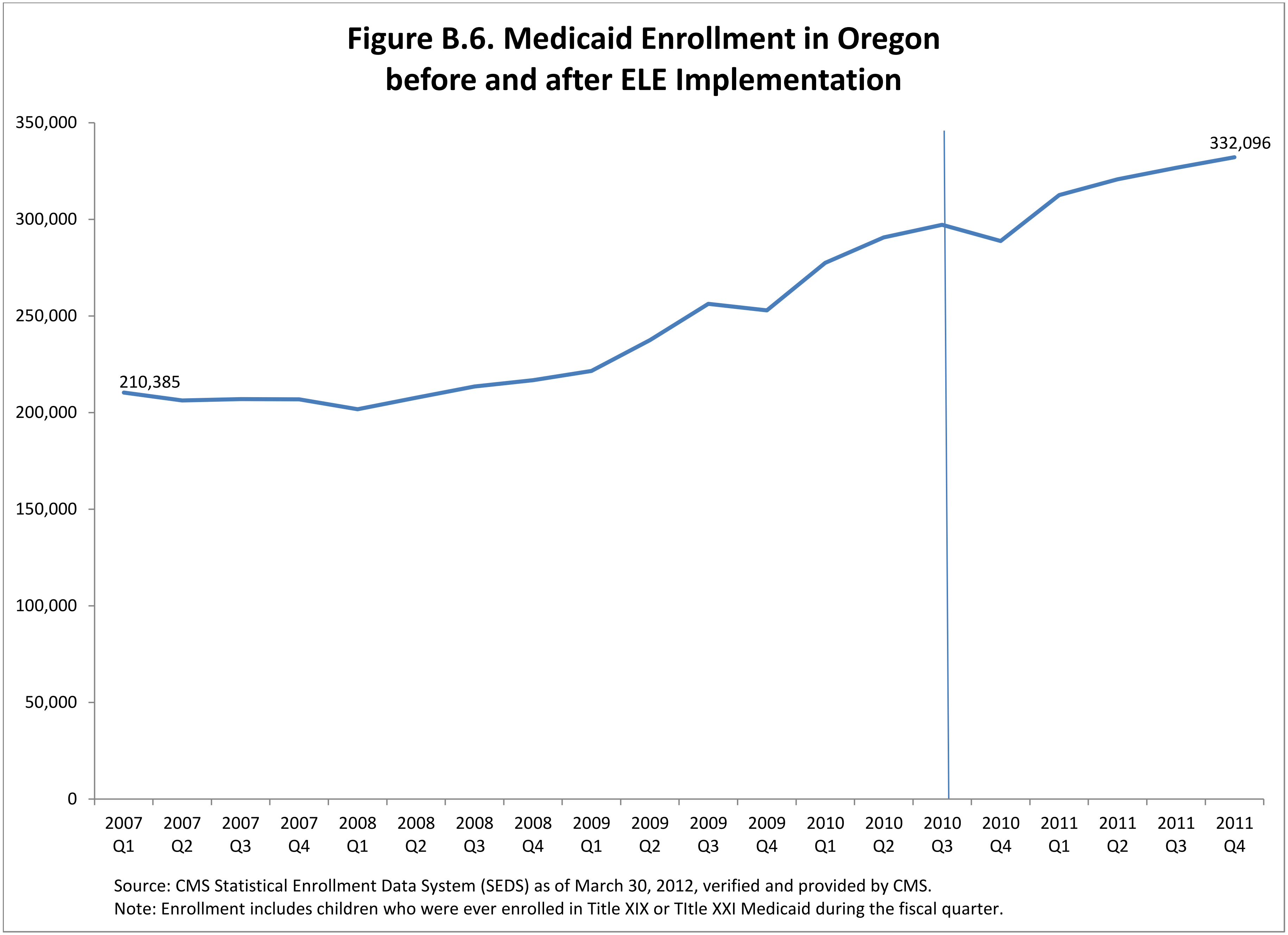
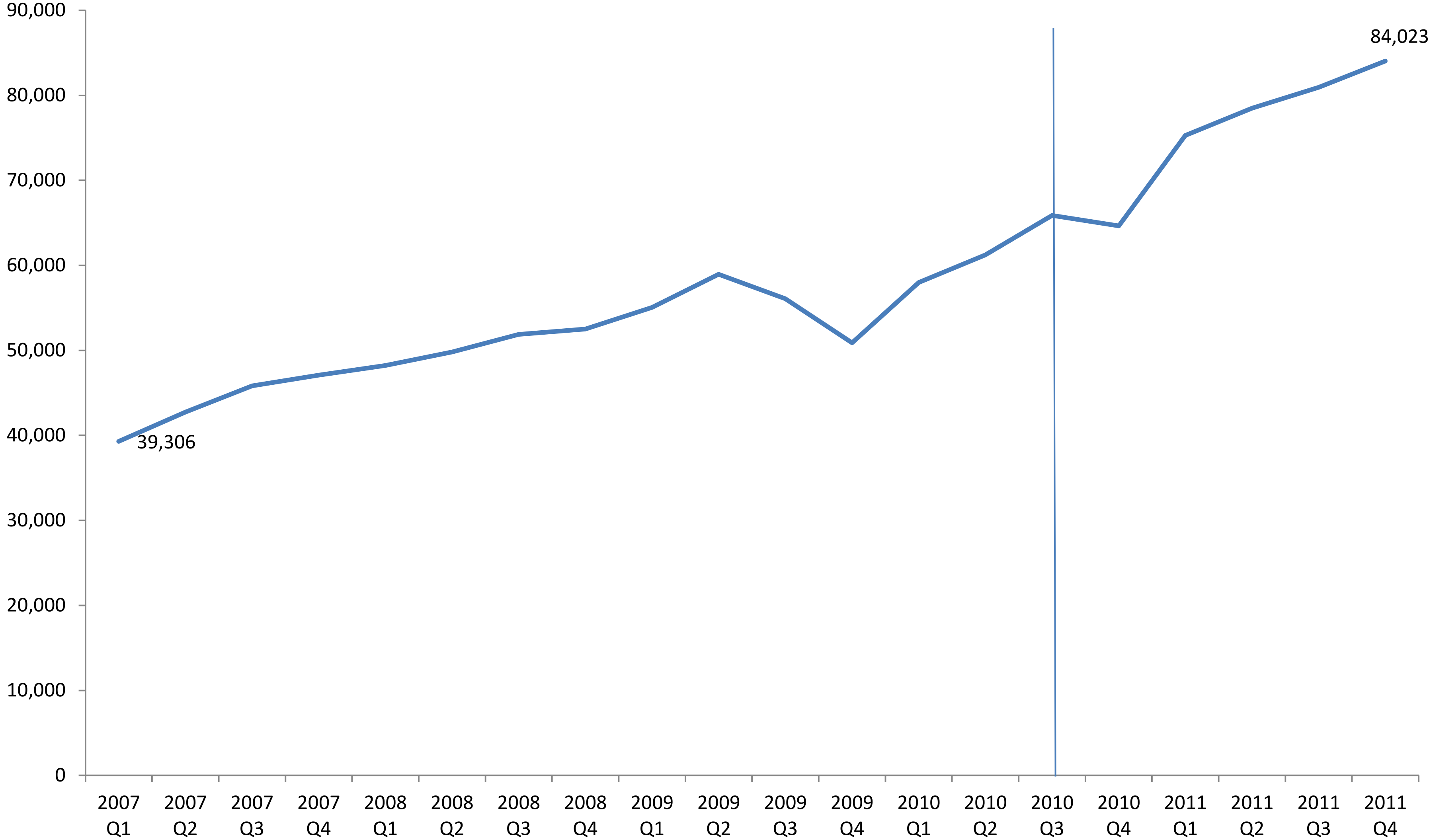


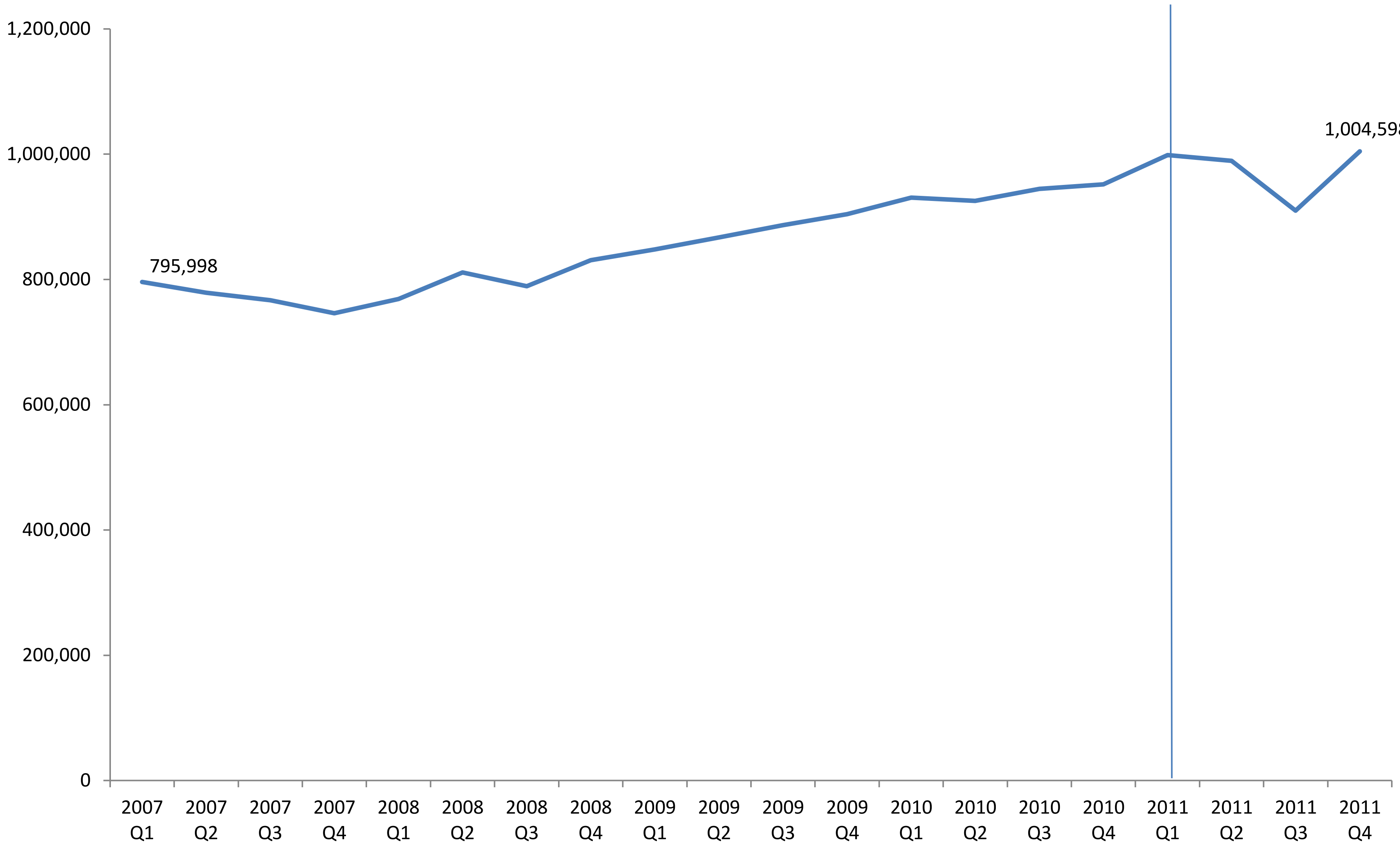
Figure B.6. Medicaid Enrollment in Oregon
before and after ELE Implementation
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
210,385
332,096
2007 Q1
2007 Q2
2007 Q3
2007 Q4
2008 Q1
2008 Q2
2008 Q3
2008 Q4
2009 Q1
2009 Q2
2009 Q3
2009 Q4
2010 Q1
2010 Q2
2010 Q3
2010 Q4
2011 Q1
2011 Q2
2011 Q3
2011 Q4
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Figure B.7. Separate CHIP Enrollment in Oregon before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in CHIP during the fiscal quarter.

Figure B.8. Medicaid Enrollment in Georgia before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

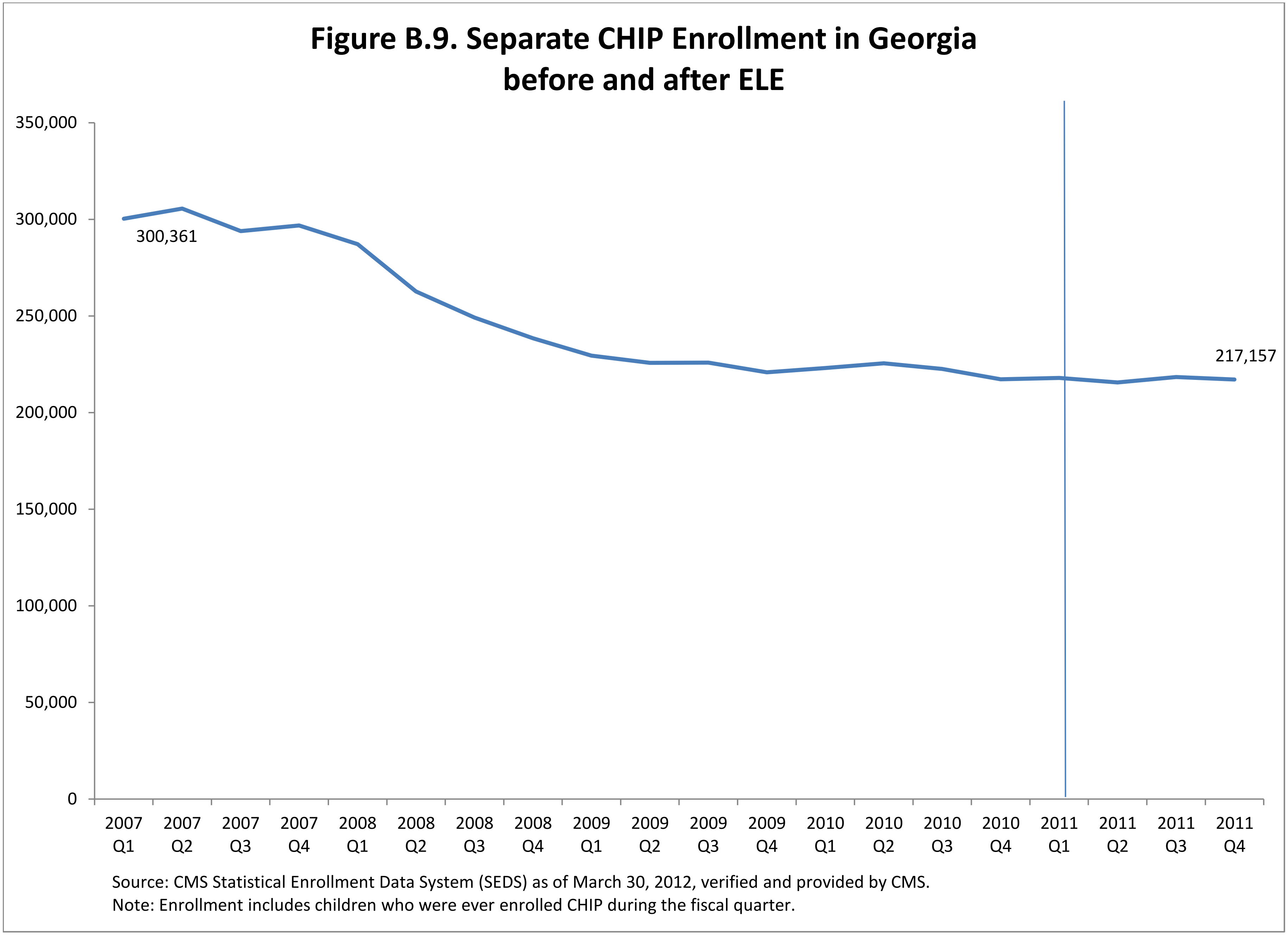
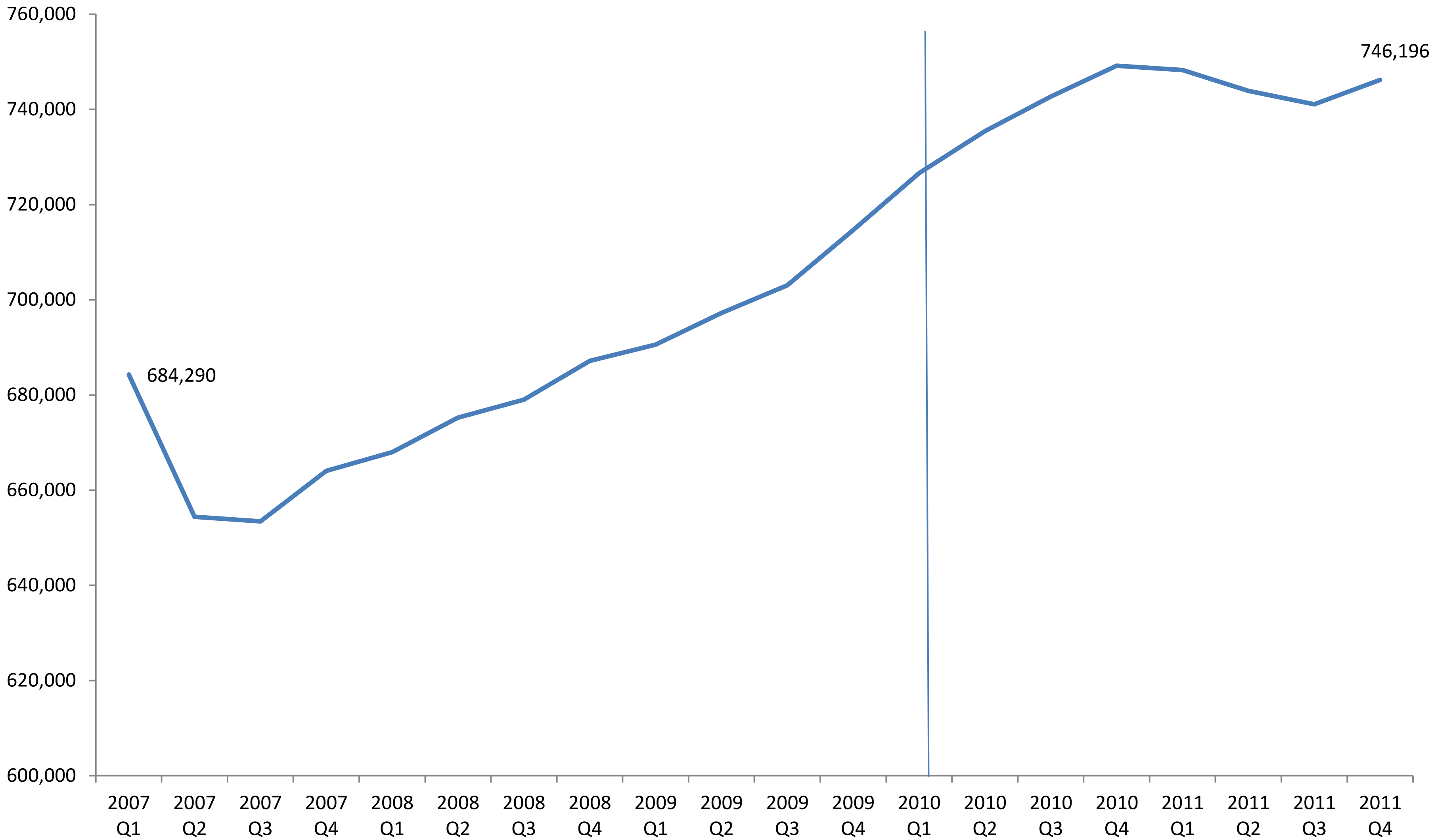


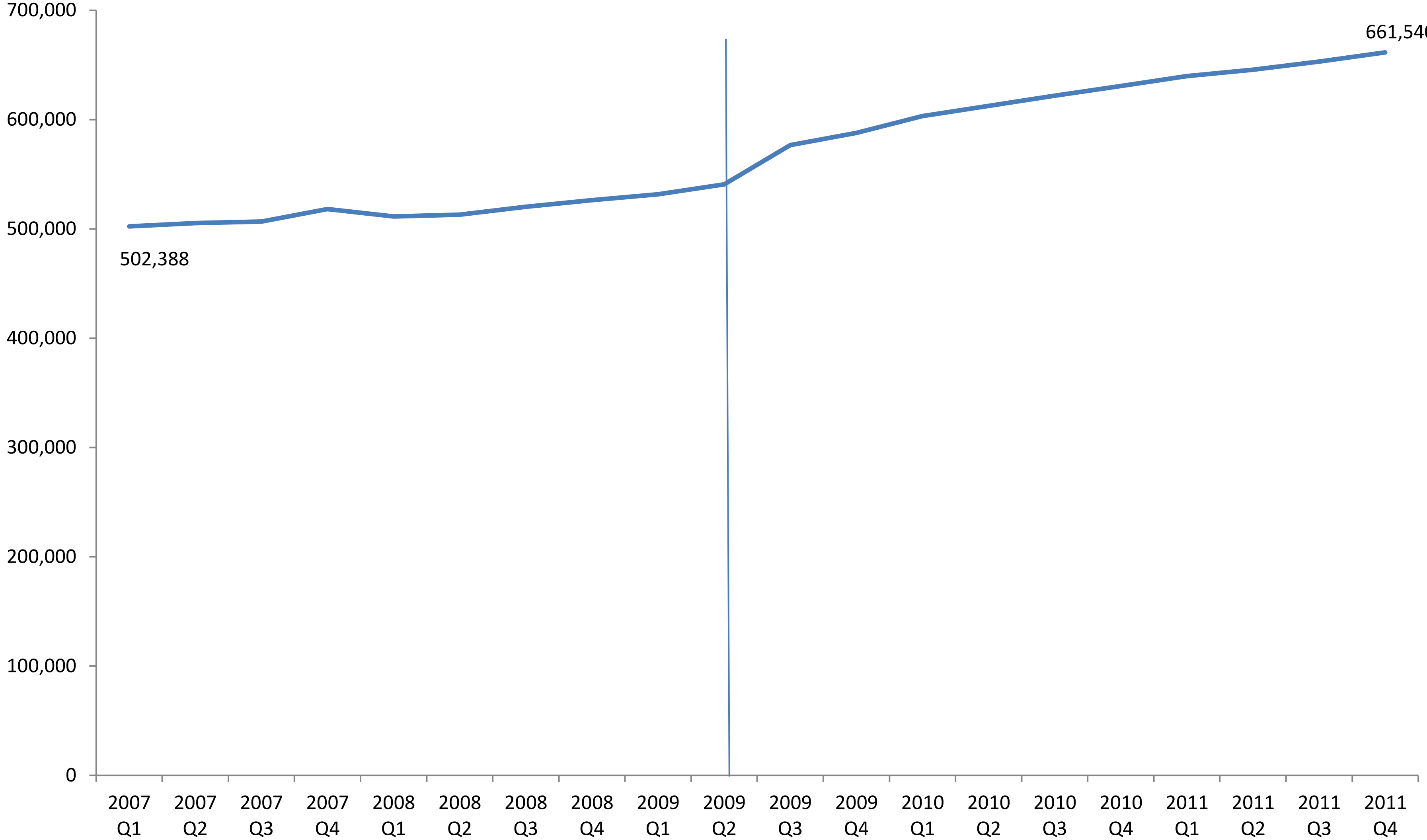
Figure B.9. Separate CHIP Enrollment in Georgia
before and after ELE
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
300,361
217,157
2007 Q1
2007 Q2
2007 Q3
2007 Q4
2008 Q1
2008 Q2
2008 Q3
2008 Q4
2009 Q1
2009 Q2
2009 Q3
2009 Q4
2010 Q1
2010 Q2
2010 Q3
2010 Q4
2011 Q1
2011 Q2
2011 Q3
2011 Q4
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled CHIP during the fiscal quarter.

Figure B.10. Medicaid Enrollment in Louisiana before and after ELE Implementation



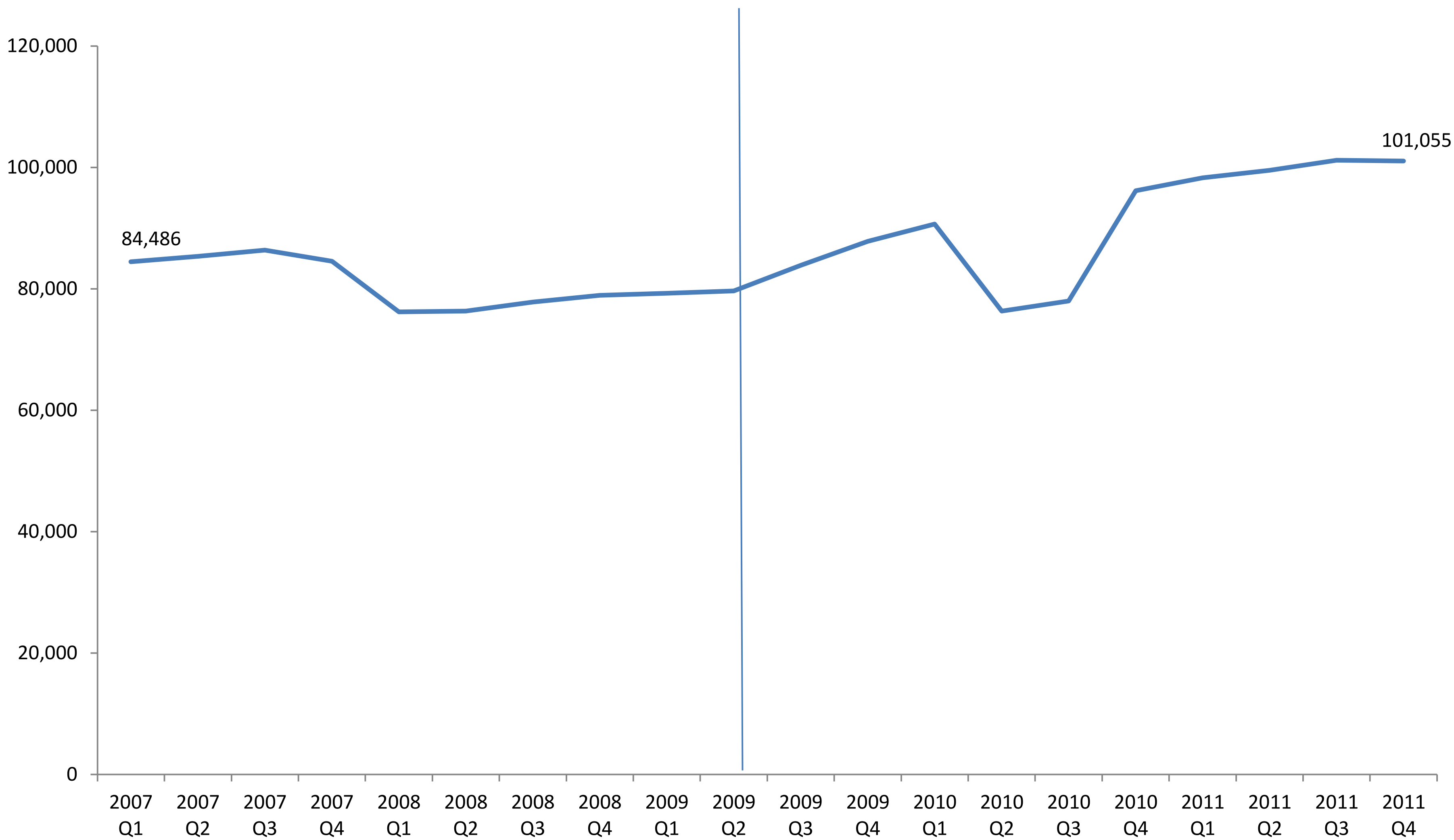
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Figure B.11. Medicaid Enrollment in New Jersey before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

Figure B.12. Separate CHIP Enrollment in New Jersey before and after ELE Implementation



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: Enrollment includes children who were ever enrolled in CHIP during the fiscal quarter.

Figure C.1a.
Medicaid/CHIP Enrollment Among ELE States, 2000-2011

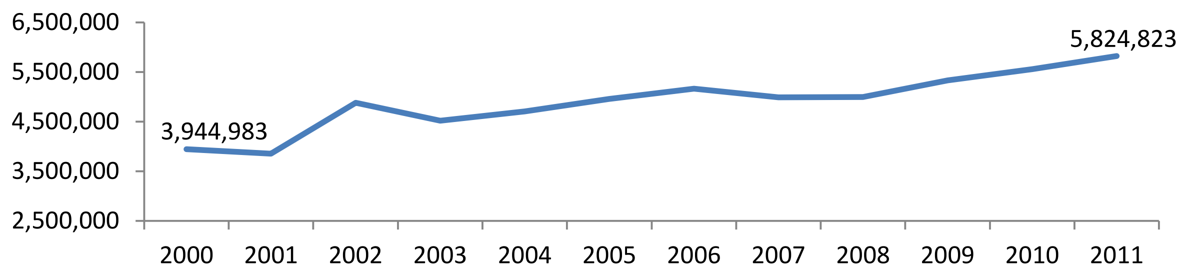
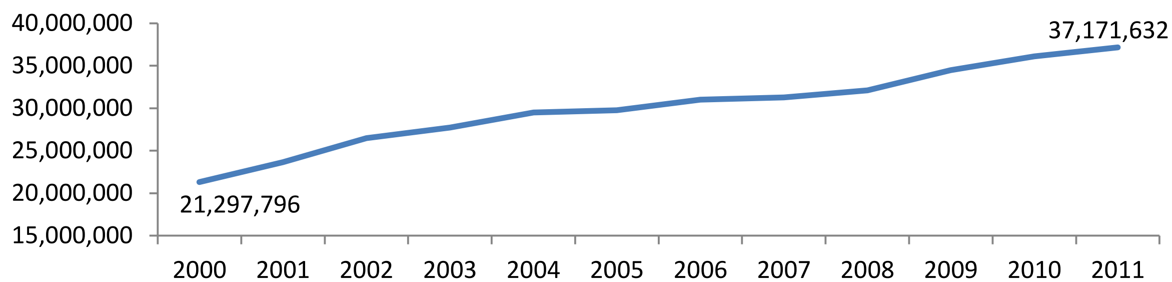


Figure C.1b.
Medicaid/CHIP Enrollment Among non-ELE States, 2000-2011



Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.
Note: (1) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal year. (2) LE states in Alabama, Georgia, Iowa, Louisiana, Maryland, New Jersey, Oregon, and South Carolina. Non-ELE states include all other states except Maine and Montana.

Table C.1. Results for Main Multivariate Regression Models Using 2006 to 2011 Annual SEDS Data

	2006 to 2011 Sample	
	Total Enrollment	**Medicaid Enrollment Only**
ELE	0.0299	0.0471
	(0.034)	(0.030)
Unemployment Rate	0.0132	0.0105
	(0.009)	(0.008)
Log(Child Population)	0.368	0.691
	(0.470)	(0.476)
Separate CHIP	-0.0108	0.0142
	(0.070)	(0.031)
Simulated Eligibility Threshold for Children	-0.0016	0.0003
	(0.002)	(0.002)
Simulated Eligibility Threshold for Parents	-0.0073	-0.0148
	(0.013)	(0.013)
Joint Application	-0.0798**	-0.0474
	(0.036)	(0.032)
Presumptive Eligibility-Medicaid	0.370***	0.0659**
	(0.069)	(0.032)
Admin. Verification of Income-Medicaid	-0.0551	0.0365*
	(0.154)	(0.018)
No In-Person Interviews-Medicaid	-0.0035	0.0071
	(0.053)	(0.045)
Continuous Eligibility-Medicaid	-0.0686	-0.0185
	(0.074)	(0.048)
Presumptive Eligibility-CHIP	-0.258***	N/A
	(0.071)	
Admin. Verification of Income-CHIP	0.0878	N/A
	(0.151)	
No In-Person Interviews-CHIP	0.106	N/A
	(0.069)	
No Asset Test-CHIP	0.151**	N/A
	(0.068)	
Continuous Eligibility-CHIP	0.0504	N/A
	(0.087)	
Constant	7.945	3.519
	(6.558)	(6.622)
R-sqr	0.99	0.99
Sample size	165	205

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and year fixed effects (coefficients not shown) (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal year Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal year (5) Montana and Maine are excluded from the sample of non-ELE states.

Table D.1. Estimated ELE Effects for Alternative Models that Add or Remove each Policy Variable
2007-2011 Quarterly SEDS Data

	Total Medicaid/CHIP Enrollment		**Medicaid Enrollment**	
	Fully adjusted main model, subtracting one policy at a time	**Unadjusted basic model, adding one policy at a time**	**Fully adjusted main model, subtracting one policy at a time**	**Unadjusted basic model, adding one policy at a time**
Main Regression Model	0.0420*		0.0562**	
	(0.024)		(0.026)	
<u>Subtracted or Added Policy Variable</u>				
Separate CHIP	0.0408*	0.0370	0.0575**	0.0375
	(0.024)	(0.029)	(0.025)	(0.026)
Simulated Eligibility Threshold for Children	0.0434*	0.0255	0.0567**	0.0389
	(0.022)	(0.024)	(0.026)	(0.025)
Simulated Eligibility Threshold for Parents	0.0296	0.0488	0.0419**	0.0539*
	(0.018)	(0.035)	(0.021)	(0.032)
Joint Application	0.0388*	0.0345	0.0519*	0.0404
	(0.022)	(0.028)	(0.026)	(0.025)
Presumptive Eligibility-Medicaid	0.0416	0.0355	0.0557**	0.0412*
	(0.025)	(0.023)	(0.027)	(0.022)
Admin. Verification of Income-Medicaid	0.0419*	0.0360	0.0512*	0.0433*
	(0.024)	(0.028)	(0.026)	(0.025)
No In-Person Interviews-Medicaid	0.0408	0.0366	0.0541**	0.0409
	(0.024)	(0.027)	(0.026)	(0.025)
Continuous Eligibility-Medicaid	0.0452*	0.0301	0.0607**	0.0378
	(0.025)	(0.024)	(0.028)	(0.023)
Presumptive Eligibility-CHIP	0.0418*	0.0342	N/A	N/A
	(0.024)	(0.025)		
Admin. Verification of Income-CHIP	0.0428	0.0368	N/A	N/A
	(0.027)	(0.028)		
No In-Person Interviews-CHIP	0.0405*	0.0358	N/A	N/A
	(0.023)	(0.029)		
No Asset Test-CHIP	0.0457*	0.0305	N/A	N/A
	(0.027)	(0.025)		
Continuous Eligibility-CHIP	0.0424*	0.0315	N/A	N/A
	(0.024)	(0.026)		
R-sqr	0.99	0.99	0.99	0.99
Sample size	660	660	820	820

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

Notes: (1) Robust standard errors clustered at the state-level are in parentheses. (2) * p<.1, ** p<.05, *** p<.01 (3) All models include state and quarter fixed effects and demographic controls (coefficients not shown) (4) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.