APPENDIX A: TECHNICAL SPECIFICATIONS

Model

To estimate the impact of the PPS on home dialysis use, we used the multivariable logistic regression model in **Equation 1**.

$$logit(Y_i) = \beta_0 + \beta_t * t_i + \beta_{MIPPA} * MIP \quad_i + \beta_{PPS} * PPS_i + \beta_{Medicare} * Medicare_i + \beta_{t*MIPPA} * t_i * MIPPA_i + \beta_{t*PPS} * t_i * PPS_i + \beta_{t*Medicare} * t_i * Medicare_i + \beta_{MIPPA*Medicare} * MIP \quad_i * Medicare_i + \beta_{PPS*Medicare} * PPS_i * Medicare_i + \beta_{t*MIPPA*Medicare} * t_i * MIPPA_i * Medicare_i + \beta_{t*PPS*Medicare} * t_i * PPS_i * Medicare_i + X_i' * \beta_X + \varepsilon_i$$

Equation 1

Where:

$$Y_i = \begin{cases} 1 \; if \; person \; i \; was \; on \; home \; dialysis \; at \; day \; 90 \\ 0 \; if \; person \; i \; was \; on \; in \; center \; hemodialysis \; at \; day \; 90 \end{cases}$$

$$logit(x) = \ln\left(\frac{x}{1-x}\right)$$

t_i is the month that person *i* started dialysis. Although we treated t_i as a continuous covariate, for each person *i*, t_i was assigned an integer value corresponding to the month of day 1 of dialysis.

$$MIPPA_i = \begin{cases} 1 \; if \; 7/9/2008 \; \leq \mathrm{t_i} \leq 12/31/2010 \\ 0 \; otherwise \end{cases}$$

$$PPS_i = \begin{cases} 1 \; if \; 1/1/2011 \leq t_i \leq 8/31/2013 \\ 0 \; otherwise \end{cases}$$

$$Medicare_i = \begin{cases} 1 \; if \; person \; i \; was \; on \; Medicare \; Parts \; A \; and \; B \; at \; day \; 90 \\ 0 \; if \; person \; i \; was \; not \; on \; Medicare \; Parts \; A \; and \; B \; at \; day \; 90 \end{cases}$$

X_i is the column vector of covariates for person *i*

β_k are the parameters that we estimated in the logistic regression for all right-hand side variables *k*. β_X is the column vector of coefficients for covariates X_i

ε_i is a random error term for person *i*

Estimating the Predicted Probability of Home Dialysis

Using these estimated parameters $\hat{\beta}_k$, we computed the average predicted probability of home dialysis at each month during the study period $\hat{Y}(t)$. In other words, we computed the predicted probability as a function of *t*, the month of interest. We estimated these probabilities under the following counterfactual conditions: (i) that the full PPS took effect, (ii) that the PPS without the training add-on took effect, and (iii) that the PPS did not take effect (**Equations 2-4**).

(i) Under the full PPS:

When $1/1/2006 \leq t \leq 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*Medicare} * t * Medicare_i$$

$$+ X_i' * \hat{\beta}_X\big)$$

Equation 2

(Note: $logit^{-1}(x) = \frac{\exp(x)}{1+\exp(x)}$)

When $7/9/2008 \leq \mathrm{t} \leq 12/31/2010$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*MIPPA} * t$$

$$+ \hat{\beta}_{t*Medicare} * t * Medicare_i + \hat{\beta}_{MIPPA*Medicare} * Medicare_i + \hat{\beta}_{t*MIPPA*Medicare} * t$$

$$* Medicare_i + X_i' * \hat{\beta}_X\big)$$

Equation 3

When $1/1/2011 \le t \le 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{fullPPS} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{PPS} + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*PPS} * t$$

$$+ \hat{\beta}_{t*Medicare} * t * Medicare_i + \hat{\beta}_{PPS*Medicare} * Medicare_i + \hat{\beta}_{t*PPS*Medicare} * t$$

$$* Medicare_i + X_i' * \hat{\beta}_X\big)$$

Equation 4

(ii) Without the training add-on:

When $1/1/2006 \le t \le 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*Medicare} * t * Medicare_i$$

$$+ X_i' * \hat{\beta}_X\big)$$

*(Identical to **Equation 2**)*

When $7/9/2008 \le \mathrm{t} \le 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly=}$$

$$= \frac{1}{N}\sum_i logi\ ^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*MIPPA} * t$$

$$+ \hat{\beta}_{t*Medicare} * t * Medicare_i + \hat{\beta}_{MIPPA*Medicare} * Medicare_i + \hat{\beta}_{t*MIPPA*Medicare} * t$$

$$* Medicare_i + X_i' * \hat{\beta}_X\big)$$

*(Identical to **Equation 3**)*

(iii) With no PPS:

For $1/1/2006 \le t \le 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{Medicare} * Medicare_i + \hat{\beta}_{t*Medicare} * t * Medicare_i + X_i' * \hat{\beta}_X\big)$$

(Identical to ***Equation 2****)*

Estimating the Marginal Effect of the PPS and Training Add-On

To estimate the marginal effect of the PPS and the training add-on at any given time point, we took the difference in the above predicted probabilities (**Equations 5-7**).

(i) Estimating the marginal effect of the full PPS

The marginal effect of the PPS depended on the time period.

When $7/9/2008 \leq \mathrm{t} \leq 12/31/2010$

$$MarginalEffect(t)_{PPS} = \hat{Y}(t)_{MIPPAonly} - \hat{Y}(t)_{noPPS}$$

Equation 5

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{PPS} = \hat{Y}(t)_{fullPPS} - \hat{Y}(t)_{noPPS}$$

Equation 6

(ii) Estimating the marginal effect of the Training Add-on

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{training\ add-on} = \hat{Y}(t)_{fullPPS} - \hat{Y}(t)_{MIPPAonly}$$

Equation 7

We used the delta method to compute 95% confidence intervals for these marginal effects.

Estimating the Predicted Probabilities and Marginal Effects in Insurance Subgroups

We estimated the same quantities for patients with Medicare Parts A and B and patients with other insurance. In order to compare the effects between each of the subgroups, we computed the predicted probabilities for the entire population under the counterfactual that the entire population had a specific type of insurance (Medicare Parts A and B or other insurance). This allowed us to control for individual characteristics that varied between each subgroup. Predicted probabilities were computed using **Equations 8-13** and marginal effects were computed using **Equations 14-19**. We estimated 95% confidence intervals using the delta method.

(i) For Patients with Medicare Parts A and B:

a. Predicted Probability Under the Full PPS

When $1/1/2006 \leq t \leq 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,MedAB} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t_i + \hat{\beta}_{Medicare} + \hat{\beta}_{t*Medicare} * t_i + X_i' * \hat{\beta}_X\right)$$

Equation 8

When $7/9/2008 \leq \mathrm{t} \leq 12/31/2010$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly,MedAB} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{Medicare} + \hat{\beta}_{t*MIPPA} * t + \hat{\beta}_{t*Medicare} * t + \hat{\beta}_{MIPPA*Medicare} + \hat{\beta}_{t*MIPPA*Medicare} * t + X_i' * \hat{\beta}_X\right)$$

Equation 9

When $1/1/2011 \leq t \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{fullPPS,MedAB} =$$

$$= \frac{1}{N}\sum_i log\quad^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{PPS} + \hat{\beta}_{Medicare} + \hat{\beta}_{t*PPS} * t + \hat{\beta}_{t*Medicare} * t$$

$$+ \hat{\beta}_{PPS*Medicare} + \hat{\beta}_{t*PPS*Medicare} * t + X_i' * \hat{\beta}_X\big)$$

Equation 10

b. Predicted Probability without the Training Add-on

When $1/1/2006 \leq t \leq 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,MedAB} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t_i + \hat{\beta}_{Medicare} + \hat{\beta}_{t*Medicare} * t_i + X_i' * \hat{\beta}_X\big)$$

*(Identical to **Equation 8**)*

When $7/9/2008 \leq \mathrm{t} \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly,MedAB} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{Medicare} + \hat{\beta}_{t*MIPPA} * t + \hat{\beta}_{t*Medicare} * t$$

$$+ \hat{\beta}_{MIPPA*Medicare} + \hat{\beta}_{t*MIPPA*Medicare} * t + X_i' * \hat{\beta}_X\big)$$

*(Identical to **Equation 9**)*

c. Predicted Probability without the PPS

For all time periods $1/1/2006 \leq t \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,MedAB} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\big(\hat{\beta}_0 + \hat{\beta}_t * t_i + \hat{\beta}_{Medicare} + \hat{\beta}_{t*Medicare} * t_i + X_i' * \hat{\beta}_X\big)$$

*(Identical to **Equation 8**)*

d. Marginal Effect of the Full PPS

When $7/9/2008 \leq \mathrm{t} \leq 12/31/2010$

$$MarginalEffect(t)_{PPS,MedAB} =$$

$$= \hat{Y}(t)_{MIPPAonly,MedAB} - \hat{Y}(t)_{noPPS,MedAB}$$

Equation 14

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{PPS,MedAB} =$$

$$= \hat{Y}(t)_{fullPPS,MedAB} - \hat{Y}(t)_{noPPS,MedAB}$$

Equation 15

e. Marginal Effect of the Training Add-on

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{training\ add-on,MedAB} =$$

$$= \hat{Y}(t)_{fullPPS,MedAB} - \hat{Y}(t)_{MIPPAonly,MedAB}$$

Equation 16

(ii) For Patients without Medicare

a. Predicted Probability Under the Full PPS

When $1/1/2006 \leq t \leq 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,noMedAB} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t_i + X_i' * \hat{\beta}_X\right)$$

Equation 11

When $7/9/2008 \leq \mathrm{t} \leq 12/31/2010$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly,noMedAB} =$$

$$= \frac{1}{N}\sum_i logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{t*MIPPA} * t + X_i' * \hat{\beta}_X\right)$$

Equation 12

When $1/1/2011 \leq t \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{fullPPS,noMedAB} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{PPS} + \hat{\beta}_{t*PPS} * t + X_i' * \hat{\beta}_X\right)$$

Equation 13

b. Predicted Probability without the Training Add-on

When $1/1/2006 \leq t \leq 7/8/2008$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,noMedAB} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t_i + X_i' * \hat{\beta}_X\right)$$

*(Identical to **Equation 11**)*

When $7/9/2008 \ \leq \mathrm{t} \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{MIPPAonly,noMedAB} =$$

$$= \frac{1}{N}\sum_{i} logit^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t + \hat{\beta}_{MIPPA} + \hat{\beta}_{t*MIPPA} * t + X_i' * \hat{\beta}_X\right)$$

*(Identical to **Equation 12**)*

c. Predicted Probability without the PPS

For $1/1/2006 \leq t \leq 8/31/2013$

$$\hat{Y}(t) = \hat{Y}(t)_{noPPS,noMedAB} =$$

$$= \frac{1}{N}\sum_{i} log \quad ^{-1}\left(\hat{\beta}_0 + \hat{\beta}_t * t_i + X_i' * \hat{\beta}_X\right)$$

*(Identical to **Equation 11**)*

d. Marginal Effect of the Full PPS

When $7/9/2008 \ \leq \mathrm{t} \leq 12/31/2010$

$$MarginalEffect(t)_{PPS,noMedAB} =$$

$$= \hat{Y}(t)_{MIPPAonly,noMedAB} - \hat{Y}(t)_{noPPS,noMedAB}$$

Equation 17

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{PPS,noMedAB} =$$

$$= \hat{Y}(t)_{fullPPS,noMedAB} - \hat{Y}(t)_{noPPS,noMedAB}$$

Equation 18

e. Marginal Effect of the Training Add-on

When $1/1/2011 \leq t \leq 8/31/2013$

$$MarginalEffect(t)_{training\ add-on,noMedAB} = \hat{Y}(t)_{fullPPS,noMedAB} - \hat{Y}(t)_{MIPPAonly,noMedAB}$$

Equation 19

Comparing the Effects of the PPS between Insurance Subgroups

We compared the effects of the PPS between patients with Medicare Parts A and B and patients with other insurance types. To perform this comparison, we employed two strategies: (a) we compared the effect of the PPS at the final month of the study period (using **Equations 14-19**) and (b) we compared the average effect of the PPS over the entire post-PPS period ("A" and "B" in **Supplemental Figure S1** respectively).

a) Comparing the Effect of the PPS at the Final Month

To determine if the PPS' effect on patients with Medicare was significantly different from the effect on other patients, we compared the marginal effect of the main policy and the training add-on in each of the subgroups. Graphically, this meant determining if the distance between the two curves in **Figure S1** at t_{end} was statistically different from 0. In other words, we defined the following null hypotheses:

$$H_{0,1}: 0 = Z_1 = MarginalEffect(t_{end})_{PPS,MedAB} - MarginalEffect(t_{end})_{PPS,noMedAB}$$

$$H_{0,2}: 0 = Z_2 = MarginalEffect(t_{end})_{training\ add-o\ \ ,MedAB}$$

$$- MarginalEffect(t_{end})_{training\ add-\ \ \ ,noMedAB}$$

Where $t_{end} = 8/31/2013$ is the last month of the study period. Each of the components of Z_1 and Z_2 were determined using **Equations 15-16** and **18-19**.

b) Comparing the Average Increase in Home Dialysis Use

Comparing the average increase in home dialysis use in each of the populations is mathematically equivalent to comparing the cumulative effect in each of the populations. The cumulative effect in each population is the integral of each curve over time in **Figure S1**, and the difference in cumulative effect is the area between the curves (B). Because cumulative effect in %-months is difficult to understand, we normalized over the time period to obtain the average % increase in home dialysis use for each subgroup. We then determined if the difference in average effect was statistically different from 0. Formally, we defined the following null hypotheses:

$$H_{0,3}: 0 = Z_3 = \frac{1}{t_{end} - t_{PPS}} \int_{t_{PPS}}^{t_{end}} \left(MarginalEffect(t)_{PPS,MedAB} - MarginalEffect(t)_{PPS,noMedAB}\right) dt$$
$$+ \frac{1}{t_{PPS} - t_{MIPPA}} \int_{t_{MIPPA}}^{t_{PPS}} \left(MarginalEffect(t)_{PPS,MedAB} - MarginalEffect(t)_{PPS,noMedAB}\right) dt$$

Equation 20

$$H_{0,4}: 0 = Z_4 = \frac{1}{t_{end} - t_{PPS}} \int_{t_{PPS}}^{t_{en}} \left(MarginalEffect(t)_{training\ add-o\ \ ,MedAB} - MarginalEffect(t)_{training\ add-on,noMedAB}\right) dt$$

Equation 21

After substituting from **Equations 14-19**, we were able to simplify the integrals further using the following result:

If $\frac{d}{dx} f(x) = c$, where c is a constant (i.e., f(x) is a linear function of x), then

$$\int log^{-1}\big(f(x)\big)dx = \frac{\ln\big(1+\exp\big(f(x)\big)\big)}{c}$$

Then:

$$Z_3 =$$

$$= \frac{1}{N}\sum_i \Bigg[\Bigg(\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{MIPPA}+\hat\beta_{Medicare}+\hat\beta_{t,MIPPA}*t+\hat\beta_{t,Medicare}*t+\hat\beta_{MIPPA,Medicare}+\hat\beta_{t,MIPPA,Medicare}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,MIPPA}+\hat\beta_{t,Medicare}+\hat\beta_{t,MIPPA,Medicare}}$$

$$-\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{MIPPA}+\hat\beta_{t,MIPPA}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,MIPPA}}\Bigg)\Big|_{t_{MIPPA}}^{t_{PPS}}$$

$$+\Bigg(\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{PPS}+\hat\beta_{Medicare}+\hat\beta_{t,PPS}*t+\hat\beta_{t,Medicare}*t+\hat\beta_{PPS,Medicare}+\hat\beta_{t,PPS,Medicare}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,PPS}+\hat\beta_{t,Medicare}+\hat\beta_{t,PPS,Medicare}}$$

$$-\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{PPS}+\hat\beta_{t,PPS}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,PPS}}\Bigg)\Big|_{t_{PPS}}^{t_{end}}$$

$$-\Bigg(\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{Medicare}+\hat\beta_{t,Medicare}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,Medicare}}-\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t}\Bigg)\Big|_{t_{MIPPA}}^{t_{end}}\Bigg]$$

And

$$Z_4 =$$

$$= \frac{1}{N}\sum_i \Bigg[\Bigg(\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{PPS}+\hat\beta_{Medicare}+\hat\beta_{t,PPS}*t+\hat\beta_{t,Medicare}*t+\hat\beta_{PPS,Medicare}+\hat\beta_{t,PPS,Medicare}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,PPS}+\hat\beta_{t,Medicare}+\hat\beta_{t,PPS,Medicare}}$$

$$-\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{MIPPA}+\hat\beta_{Medicare}+\hat\beta_{t,MIPPA}*t+\hat\beta_{t,Medicare}*t+\hat\beta_{MIPPA,Medicare}+\hat\beta_{t,MIPPA,Medicare}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,MIPPA}+\hat\beta_{t,Medicare}+\hat\beta_{t,MIPPA,Medicare}}\Bigg)$$

$$-\Bigg(\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{PPS}+\hat\beta_{t,PPS}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,PPS}}-\frac{\ln\big(1+exp\big(\hat\beta_0+\hat\beta_t*t+\hat\beta_{MIPPA}+\hat\beta_{t,MIPPA}*t+X_i'*\hat\beta_X\big)\big)}{\hat\beta_t+\hat\beta_{t,MIPPA}}\Bigg)\Bigg]\Big|_{t_{PPS}}^{t_{end}}$$

Where $t_{MIPPA} = 7/9/2008$, $t_{PPS} = 1/1/2011$, and $t_{end} = 8/31/2013$

c) Statistical Inference

Because we used multiple imputation for our primary analysis, we employed Rubin's rules to combine imputed results into a single point estimate.[1] For each of the imputed datasets (denoted $m = 1, \ldots, M$, where M = 20 is the total number of imputations), we computed the above statistics of interest (which we define as $Z_{j,m}$ for the $j = 1, \ldots, 4$ statistics and M imputations) and took the arithmetic mean.

We used non-parametric bootstrap 95% confidence intervals to assess if the difference-in-differences estimates were statistically significant. Schomaker and Heumann suggest that in order to obtain the correct standard errors we should first draw $b = 1, \ldots, B$ bootstrap samples from the original dataset *with* missing values, then perform $m_b = 1, \ldots, M_B$ imputations on the bootstrapped dataset.[2] The sampling-imputation process yields *B x* M_B bootstrapped-imputed datasets, from which we computed the statistics Z_{j,b,m_b} for $j = 1, \ldots, 4$. To find confidence intervals, we took the 2.5% and 97.5% quantiles of each of these *B x* M_B statistics. (Notably, for each b, one could first compute $Z_{j,b} = \frac{1}{M_B} \sum_{m_b} Z_{j,b,m_b}$, then take the 2.5% and 97.5% quantiles of $Z_{j,b}$. Schomaker and Heumann suggest that this approach yields confidence intervals that are too wide). Since each of the statistics Z_{j,b,m_b} were treated similarly and because the bootstrap samples were drawn randomly with replacement, we chose to perform one imputation ($M_B = 1$) for each of the bootstrapped samples. We drew B = 1,000 bootstrapped samples.

SUPPLEMENTAL TABLES AND FIGURES

Table S1: Definitions of Outliers and Number of Patients in the Sample

Characteristic	Cutoff	Patients with Outlier	
		N	**%**
Age	> 110	12	0%
Albumin	< 0.5	37,306	3.5%
Albumin	> 5.5	3,242	0.3%
Hemoglobin	< 5	4,329	0.4%
Hemoglobin	> 20	4,344	0.4%

Abbreviations: BMI = Body Mass Index

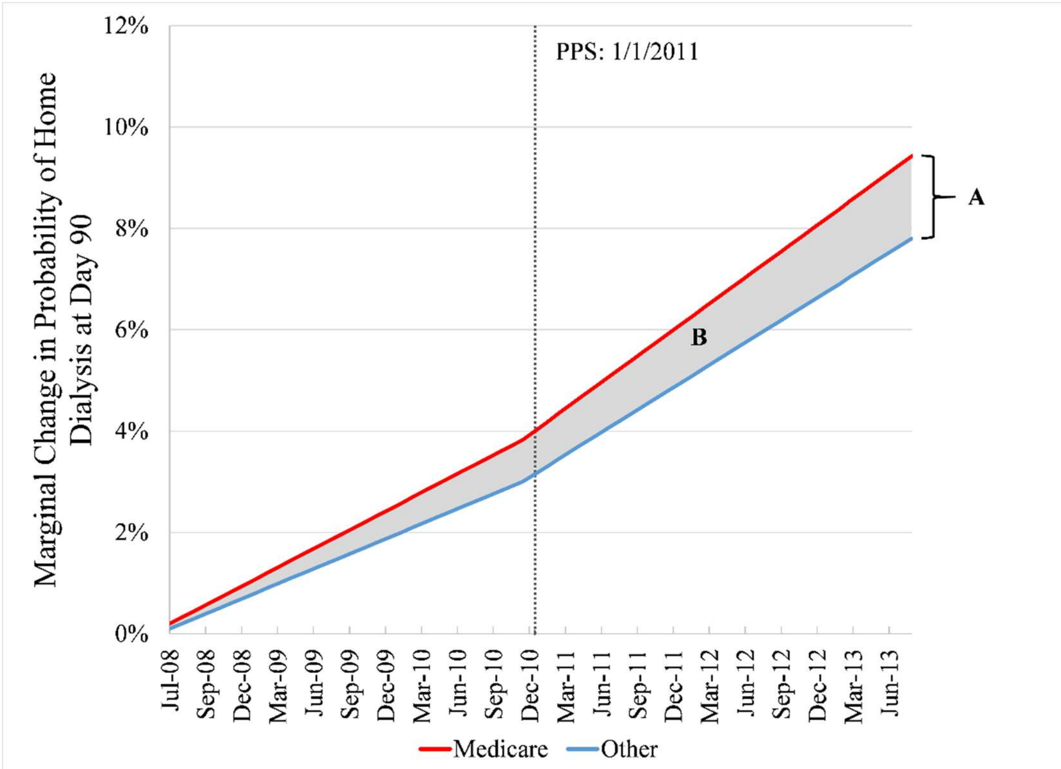
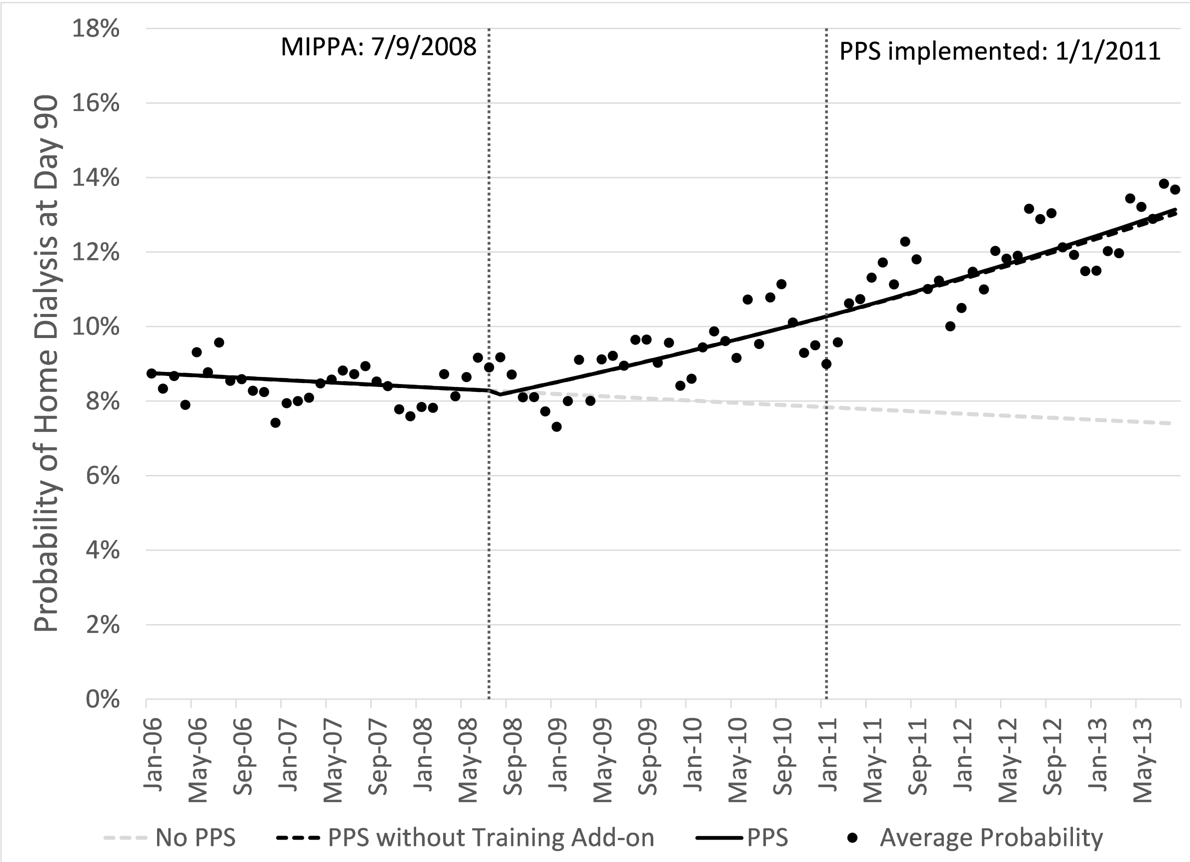


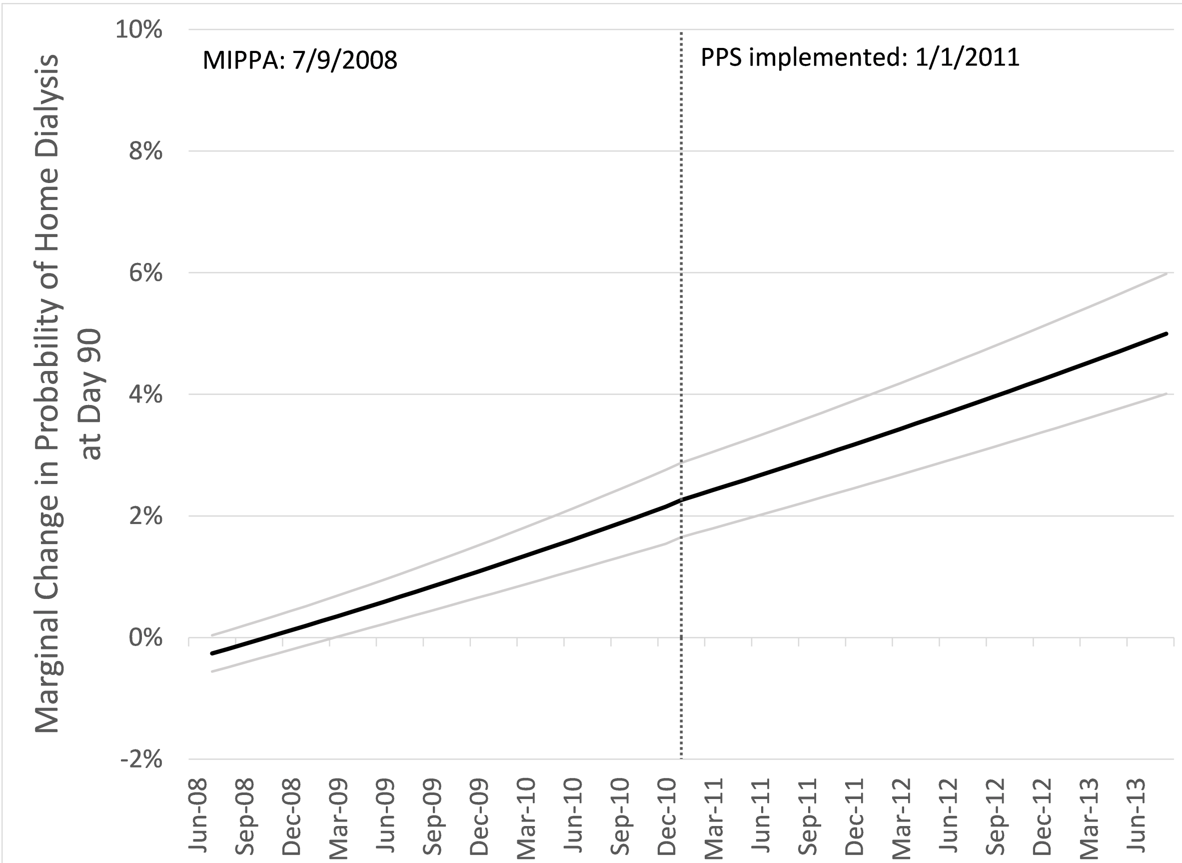
Figure S1: A graphical example illustrating the policy effect between the Medicare and non-Medicare populations. Letter “A” corresponds to the difference in policy effect between the two populations at the last month. Letter “B” represents the difference in cumulative effect between the two populations in the post-policy period.

S2A



MIPPA: 7/9/2008
PPS implemented: 1/1/2011
Probability of Home Dialysis at Day 90
18%
16%
14%
12%
10%
8%
6%
4%
2%
0%
Jan-06
May-06
Sep-06
Jan-07
May-07
Sep-07
Jan-08
May-08
Sep-08
Jan-09
May-09
Sep-09
Jan-10
May-10
Sep-10
Jan-11
May-11
Sep-11
Jan-12
May-12
Sep-12
Jan-13
May-13
No PPS
PPS without Training Add-on
PPS
Average Probability

S2B



10%
8%
6%
4%
2%
0%
-2%
MIPPA: 7/9/2008
PPS implemented: 1/1/2011
Marginal Change in Probability of Home Dialysis at Day 90
Jun-08
Sep-08
Dec-08
Mar-09
Jun-09
Sep-09
Dec-09
Mar-10
Jun-10
Sep-10
Dec-10
Mar-11
Jun-11
Sep-11
Dec-11
Mar-12
Jun-12
Sep-12
Dec-12
Mar-13
Jun-13

S2C

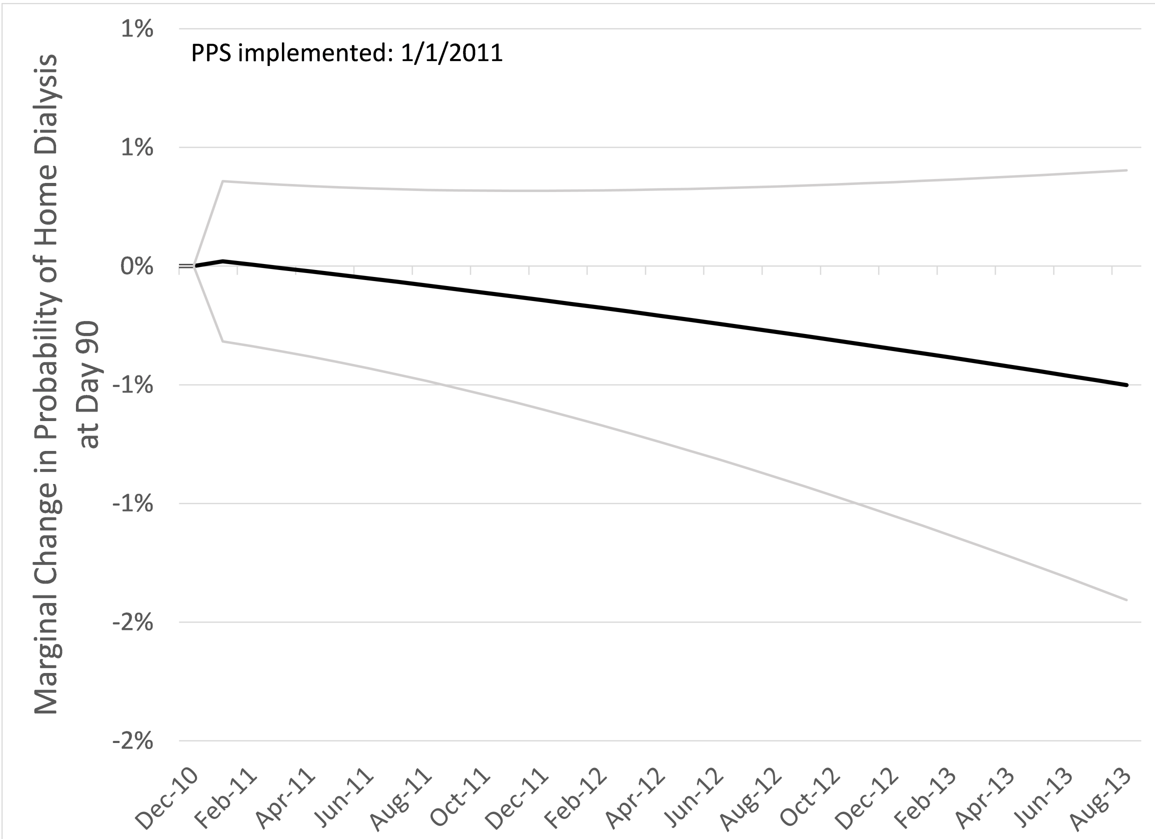


Figure S2. Effect of the Prospective Payment System (PPS) on home dialysis use at day 90 in incident End-Stage Renal Disease (ESRD) patients. **Panel A** shows the unadjusted probability of home dialysis at day 90 over time. The scatter plot indicates the average proportion of the population utilizing home dialysis at day 90. Under the PPS (solid black line), the predicted probability of home dialysis increased substantially after passage of the Medicare Improvement for Patients and Providers Act (MIPPA). The projected probability of home dialysis was similar for the PPS without the training add-on (dotted black line). We projected a decline in home dialysis use if the PPS had not taken effect (dotted gray line). **Panel B** shows the overall effect of the PPS over time, or the difference between the predicted probability of home dialysis under the PPS and without the PPS (effect in solid black with 95% confidence intervals in gray). The PPS continued to exert a positive, increasing effect on home dialysis utilization, with a net positive effect of 5% by the end of the study period. In **Panel C**, we plot the effect of the PPS's training add-on, or the difference between the predicted probability of home dialysis under the PPS and the projected probability without the training add-on (effect in solid black with 95% confidence intervals in gray). The effect from the training add-on was not statistically significant.

APPENDIX REFERENCES

1. Rubin, D. B. *Multiple Imputation for Nonresponse in Surveys*. (John Wiley & Sons, 1987).
2. Schomaker, M. & Heumann, C. Bootstrap Inference when Using Multiple Imputation. *ArXiv Prepr. ArXiv160207933* (2016).