Reducing Medical Spending of The Publicly Insured: The Case for A Cash-out Option (Online Appendix)

By Svetlana Pashchenko Ponpoje Porapakkarm*

Appendix A. Implementation of the optimal allocation

The example of the implementation of the optimal allocation suggested in Section II works if $T_1 = c_L^* + m_L^* \geq c_H^* + q_2(m_H^*)m_H^* = T_2$. To satisfy this condition, we need to put some parametric restrictions on the problem. We consider the following parametrization:

$$u(x) = v(x) = \begin{cases} \dfrac{x^{1-\sigma}}{1-\sigma} & ; \text{ if } \sigma > 1 \\ \log(x) & ; \text{ if } \sigma = 1 \end{cases}$$

i.e., individuals' preferences over nonmedical and discretionary medical consumption can be described by the CRRA (or log) function. In addition, we assume the medical need of the L-type is zero, i.e., $\eta_L = 0$.

We introduce the following notation:

$$\gamma = \frac{c_H^*}{c_L^*}$$
$$\alpha = \frac{m_H^*}{c_L^*}$$

Note that because $c_H^* < c_L^*$ (see Section II), we have $\gamma \leq 1$. Also, because $u(\cdot) = v(\cdot)$, from Eq.(8) we have that $c_L^* = m_L^*$. Because $m_H^* > m_L^* = c_L^*$, we have $\alpha \geq 1$. Expressing m_L^*, c_H^* and m_H^* in terms of c_L^*, we can write the ICC in Eq.(3) as follows:

* Pashchenko: Terry College of Business, University of Georgia, 620 South Lumpkin Street, Athens, GA 30602 (email: svetlana@uga.edu); Porapakkarm: National Graduate Institute for Policy Studies (GRIPS), 7-22-1 Roppongi, Minato-ku, Tokyo 106-8677 (email: p-porapakkarm@grips.ac.jp). We thank Charles Brendon, Mariacristina De Nardi, Eric French, Mike Golosov, Oleg Itshoki, John Kennan, Jean-Marie Lozachmeur, Yoki Okawa, Nicola Pavoni, Matthew Shapiro, Ali Shourideh, Motohiro Yogo, and all seminar participants at the Asian Meeting of the Econometric Society in Hong Kong, CIREQ Macro Conference, IFS, Keio-GRIPS Macroeconomics and Policy Workshop, Midwest Macro Meeting in Kansas City, QSPS Summer Workshop, and World Congress in Montreal for their comments and suggestions. All errors are our own.

$$\left\{ \begin{array}{ll} 2\frac{c_L^{*1-\sigma}}{1-\sigma} = \frac{(\gamma c_L^*)^{1-\sigma}}{1-\sigma} + \frac{(\alpha c_L^*)^{1-\sigma}}{1-\sigma} & ;\ \text{if } \sigma > 1 \\ 2\log(c_L^*) = \log(\gamma c_L^*) + \log(\alpha c_L^*) & ;\ \text{if } \sigma = 1 \end{array} \right\}$$

or

$$\left\{ \begin{array}{ll} \alpha = \left(2 - \gamma^{1-\sigma}\right)^{1/(1-\sigma)} & ;\ \text{if } \sigma > 1 \\ \alpha = \gamma^{-1} & ;\ \text{if } \sigma = 1 \end{array} \right\}$$

Note that in the case of $\sigma > 1$, $\gamma^{1-\sigma} < 2$ or $\gamma > 2^{1/(1-\sigma)}$. We can rewrite the expression for wedge q in terms of α and γ as follows:

$$q = \left\{ \begin{array}{ll} \dfrac{1 + \left(\frac{\alpha}{\gamma}\right)^{-\sigma} \pi(\gamma^{-\sigma} - 1)}{1 + \pi(\gamma^{-\sigma} - 1)} & ;\ \text{if } \sigma > 1 \\ \dfrac{1 + \left(\frac{\alpha}{\gamma}\right)^{-1} \pi(\gamma^{-1} - 1)}{1 + \pi(\gamma^{-1} - 1)} & ;\ \text{if } \sigma = 1 \end{array} \right\}$$

Next, we can rewrite the inequality of interest $c_L^* + m_L^* \geq c_H^* + q_2(m_H^*)m_H^*$ as follows:

$$\left\{ \begin{array}{ll} 2 \geq \gamma + \dfrac{1 + \left(\frac{\alpha}{\gamma}\right)^{-\sigma} \pi(\gamma^{-\sigma} - 1)}{1 + \pi(\gamma^{-\sigma} - 1)}\alpha & ;\ \text{if } \sigma > 1, \\ 2 \geq \gamma + \dfrac{1 + \left(\frac{\alpha}{\gamma}\right)^{-1} \pi(\gamma^{-1} - 1)}{1 + \pi(\gamma^{-1} - 1)}\alpha & ;\ \text{if } \sigma = 1, \end{array} \right\}$$

which can be rearranged as follows:

$$\left\{ \begin{array}{ll} \dfrac{2 - \gamma - \left(2 - \gamma^{1-\sigma}\right)^{1/(1-\sigma)}}{2 - \gamma^{\sigma} - \gamma^{-\sigma}} \leq 2\pi & ;\ \text{if } \sigma > 1 \\ \dfrac{2 - \gamma - \gamma^{-1}}{2 - \gamma - \gamma^{-1}} \leq 2\pi & ;\ \text{if } \sigma = 1 \end{array} \right\}$$

Note that the inequality sign changes direction because we divide both sides by $2 - \gamma^{\sigma} - \gamma^{-\sigma}$ (or $2 - \gamma - \gamma^{-1}$ in the case of log-utility), which is negative.

For the case of log-utility ($\sigma = 1$), the condition $c_L^* + m_L^* \geq c_H^* + q_2(m_H^*)m_H^*$ is satisfied when $\pi > 1/2$, i.e., there are more healthy individuals (with low medical need) than unhealthy individuals. For a more general case ($\sigma > 1$), the expression

$$\frac{2 - \gamma - \left(2 - \gamma^{1-\sigma}\right)^{1/(1-\sigma)}}{2 - \gamma^{\sigma} - \gamma^{-\sigma}}$$

is less than one except for values of γ close to $2^{1/(1-\sigma)}$, which implies a very high value of α inconsistent with the resource constraint. Thus, for the CRRA function, the restriction on π that makes the condition $c_L^* + m_L^* \geq c_H^* + q_2(m_H^*)m_H^*$ hold is less strict than for the log-utility, i.e., it is true even for values of $\pi < 1/2$. Overall, when using the CRRA (or log) parametrization of the utility from nonmedical and discretionary medical consumption, our implementation mechanism works provided that a large enough fraction of individuals are healthy (at least more than half).

Appendix B. Alternative model of utility from medical consumption

In this section, we discuss the performance of the estimated/calibrated model where the utility over medical consumption takes the following form:

$$v(m, \eta) = \theta \frac{(m - \eta)^{1-\sigma}}{1 - \sigma},$$

where θ is greater than zero.

Apart from the functional form for the utility of medical consumption, the model is identical to the one described in the main text. We use the same approach to estimate/calibrate the parameters of the model as described in Section IV. The only exception is that now medical consumption does not have a saturation point, so instead of parameter Δ we need to estimate the multiplier θ. The parameter θ affects the marginal utility, and therefore determines the demand for discretionary medical consumption. We calibrate θ by targeting the difference in medical spending between the privately insured and the uninsured, the same moment we use to identify the parameter Δ in the main text.

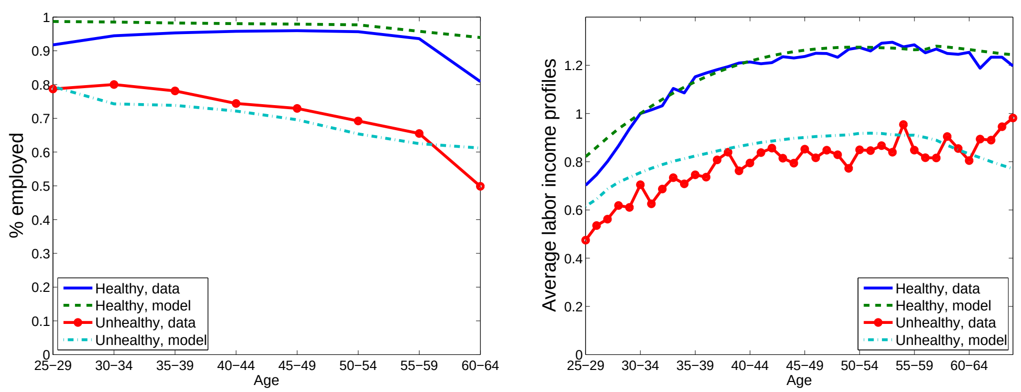

Figure B1. : Employment and average labor income among workers

Note: Labor income is normalized by average income. Solid line (line with round markers): data for the healthy (unhealthy) from the MEPS data. Dashed (dash-dotted) line: model for the healthy (unhealthy).

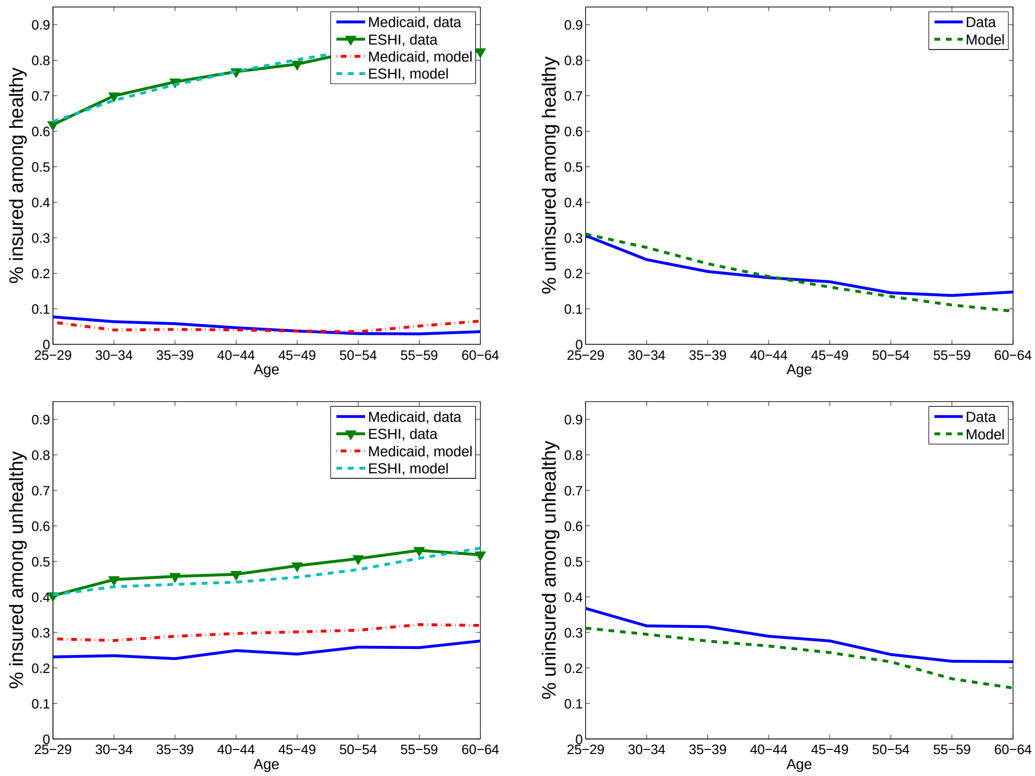

Figure B2. : Insurance profiles for the healthy

Note: Top (bottom) panels show insurance profiles for the healthy (unhealthy). Solid lines and lines with triangle markers are from the MEPS data. Dotted and dash-dotted lines are from the model. ESHI is "employers' sponsored insurance".

Figures (B1), (B2), (B3), and (B4) compare the moments related to health insurance, employment, labor income and medical spending by health and insurance constructed from the data and the calibrated model. Overall, the alternative model can capture many salient features of the data, but it produces income and price elasticities that are too high.

The implied income elasticity of medical spending in the alternative model is 1.17, which is significantly higher than its empirical counterpart (0-0.2 as discussed in Section III.B. Our baseline model produces an elasticity of 0.13. The income elasticity was computed in the same way as in Section III.B.

As for the price elasticity, we cannot compute it in the same way as for the baseline model in Section III.B. In that section to reproduce the setup of the RAND health insurance experiment, we compare medical spending between two experiments with universal health insurance that cover 100 and 75 percent of spending. In the alternative model discussed in this section, we cannot compute

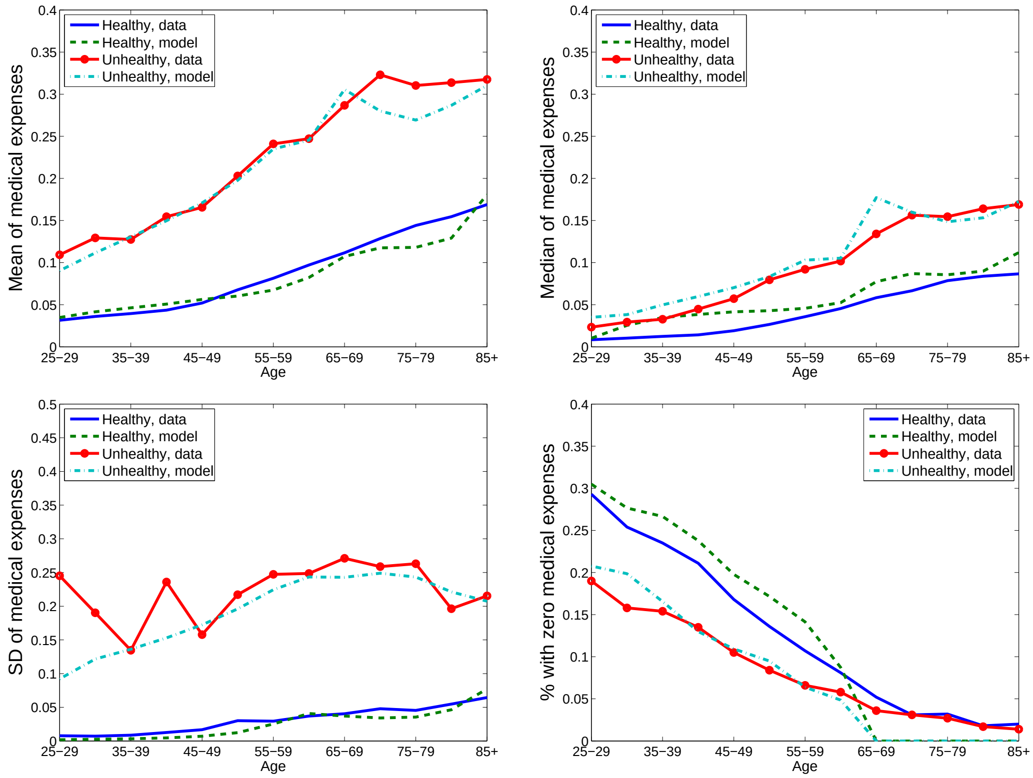

Figure B3. : Medical expenses by health

Note: Top left (right) panel shows average (median) medical expenses by health. Bottom left and right panels show standard deviation of medical expenses and fraction of people with zero medical expenses by health, respectively. Solid lines (lines with round markers) are from the MEPS data for the healthy (unhealthy). Dashed (dash-dotted) lines are from the model for the healthy (unhealthy). All level variables are normalized by average income.

medical spending when health insurance provides full coverage. The consumer optimization problem does not have a solution because the marginal utility of medical consumption is always positive while the marginal costs are zero. To avoid this, we compare two health insurance schemes that cover 95 and 75 percent of medical spending. The resulting reduction in medical spending when moving from more to less generous coverage constitutes a 53 percent decrease, while the corresponding decrease is 16 percent in the RAND experiment and 18 percent in our baseline model. Because both price and income elasticities are important for our policy analysis, we chose the model with the CRRA and a saturation point in the main text.

Another possible way to model the utility from medical consumption is to use

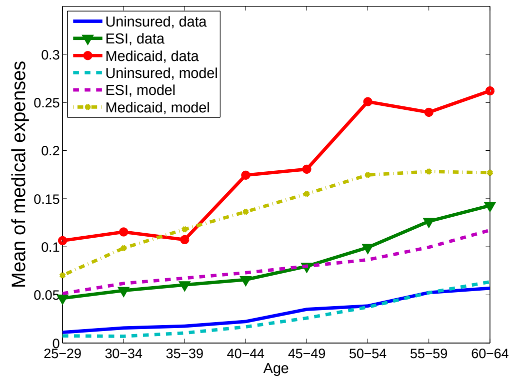

Figure B4. : Average medical expenses by insurance status

Note: All numbers are normalized by average income. Solid lines (with or without markers) are from the MEPS data. Dashed and dash-dotted lines are from the model. ESI stands for employer-sponsored insurance.

the CRRA function with a different risk aversion. Specifically, we could consider

$$v(m,\eta) = \frac{(m-\eta)^{1-\sigma^M}}{1-\sigma^M}, \tag{B1}$$

where σ^M can be different from the risk aversion over nonmedical consumption σ. The problem with this specification, however, is that σ^M is difficult to identify from the data. We use the following example as an illustration.

Consider the following static problem of an individual with medical need η who allocates his endowment I between nonmedical (c) and medical (m) consumption:

$$\max_{c,m} \frac{c^{1-\sigma}}{1-\sigma} + v(m,\eta)$$

s.t.

$$c + m = I$$

The first-order condition for this problem when using the CRRA specification in Eq.(B1) can be written as:

$$(I-m)^{-\sigma} = (m-\eta)^{-\sigma^M}.$$

The utility from medical consumption depends on two parameters: η and σ^M. In our calibration, we want to match two moments: observed medical spending m^{obs} and the effect of insurance on medical spending. The latter depends on the fraction of nondiscretionary spending in total medical spending, i.e., $\frac{\eta}{m}$. Thus, we only have one free parameter, σ^M, to match the observed spending. Note that from the first order condition it follows that an increase in σ^M can either increase or decrease total medical spending, which depends on the value of medical need η.[1] Because our model allows for heterogeneity in medical needs, the effect of changing σ^M on total medical spending is undetermined.

Appendix C. Additional statistics for policy simulations (one-time policy change)

In Section VI.B we compare the effects of two types of policies on total medical spending: a uniform reduction in Medicaid generosity versus a division of Medicaid into in-kind and in-cash subprograms. In this section, we consider the effects of these policies on out-of-pocket medical spending for all individuals younger than 65 years old. In the analysis below, we focus on the one-time policy change.

Table C1 reports the change in the mean and standard deviation of out-of-pocket medical spending when Medicaid generosity is uniformly reduced. Table C2 reports the same statistics when the cash-out option is introduced and the generosity of traditional (in-kind) Medicaid is reduced. Row 1 of each table reports the results for the full information case as a reference.

Both tables demonstrate a similar pattern: as Medicaid coinsurance increases, both the mean and standard deviation of out-of-pocket spending grow larger. As Tables 3 and 4 in the main text show, we can achieve the same reduction in total medical spending as in the full information case by either increasing the Medicaid coinsurance rate to 60 percent or by increasing it to 30 percent and introducing the cash-out option. In the former case the corresponding increase in the average out-of-pocket spending is the same as in the full information economy (20 percent), while in the latter case it is somewhat smaller (16 percent). The smaller increase in the average out-of-pocket spending in the case of the cash-out option occurs for the following reason. In the full information economy, all discretionary medical expenses are paid out-of-pocket while all necessary expenses are covered. In the case with a cash-out option, those who enroll in traditional Medicaid have only 70 percent of their necessary medical expenses covered (which increases their out-of-pocket spending compared with the full information case) but they are responsible for only 30 percent of their discretionary expenses (which decreases their out-of-pocket spending). The latter effect quantitatively exceeds the former.

As for the change in the standard deviation, the full information case and the case with a cash-out option and 30 percent Medicaid coinsurance rate are similar:

[1]This can be shown by differentiating the first-order condition with respect to σ^M:

$$\frac{\partial m}{\partial \sigma^M} = -\frac{ln\,(m-\eta)}{\frac{\sigma^M}{m-\eta} + \frac{\sigma}{I-m}}.$$

The derivative can be positive or negative depending on whether $m-\eta$ is greater or less than one.

the standard deviation increases by 7.6 and 6.7 percent, respectively. In the case where the Medicaid coinsurance rate is 60 percent and there is no cash-out option, the increase in the standard deviation is higher at 9.7 percent because people in this case are more exposed to the risk of high out-of-pocket medical expenses.

Table C1—: The effects of increasing Medicaid coinsurance on out-of-pocket medical spending, *one-time policy change*

	Change in out-of-pocket spending (percent of BS)	
	Average	Standard deviation
Baseline (BS)	0.0	0.0
1. Observable medical need	20.2	7.6
Increasing Medicaid coinsurance		
2. Medicaid covers 90%	4.8	0.6
3. Medicaid covers 80%	9.6	2.4
4. Medicaid covers 70%	13.4	4.6
5. Medicaid covers 60%	16.3	6.4
6. Medicaid covers 50%	18.7	8.1
7. Medicaid covers 40%	20.5	9.7

Table C2—: The effects of introducing a cash-out option on out-of-pocket medical spending, *one-time policy change*.

	Change in out-of-pocket spending (percent of BS)	
	Average	Standard deviation
Baseline (BS)	0.0	0.0
1. Observable medical need	20.2	7.6
Increasing Medicaid coinsurance		
2. Medicaid covers 97%	0.4	0.0
3. Medicaid covers 90%	4.8	1.0
4. Medicaid covers 80%	11.3	3.8
5. Medicaid covers 70%	16.2	6.7

Table C3 provides additional statistics to better illustrate the sorting created by the division of Medicaid into the in-cash and in-kind subprograms. The second and third columns of the table report the average out-of-pocket spending separately for enrollees of each subprogram. Not surprisingly, people who opt out of traditional Medicaid have substantially lower out-of-pocket spending. For example, when traditional Medicaid covers 90 percent of medical costs its enrollees pay \$1,177 out-of-pocket while this number is only \$173 for the participants of the cash subprogram.

Table C3—: Characteristics of Medicaid beneficiaries when the cash-option is introduced, *one-time policy change.*

	Out-of-pocket spending ($)		$\eta_t^h < 75^{th}$ percentile
	cash option	Traditional Medicaid	(Traditional Medicaid)
Medicaid covers 97%	75	341	24%
Medicaid covers 90%	173	1,177	10%
Medicaid covers 80%	494	2,258	2%
Medicaid covers 70%	882	3,143	0%

Note: The 2^{nd} and 3^{rd} columns show average out-of-pocket medical spending. The 4^{th} column shows the fraction of enrollees in the in-kind Medicaid subprogram whose medical need (η_t^h) is below the 75^{th} percentile of the medical need distribution among Medicaid enrollees.

Column 4 of Table C3 illustrates the composition of enrollees in the traditional Medicaid subprogram. Specifically, it reports the percentage of enrollees who are in the bottom 75 percent of the medical need distribution among Medicaid beneficiaries. Note that since medical need represents unavoidable or necessary spending, the top 25 percent of its distribution can be roughly categorized as those with catastrophic expenses. Table C3 illustrates that as the generosity of traditional Medicaid decreases and the size of transfers in the cash subprogram increases, individuals with noncatastrophic medical spending switch to the cash option. When traditional Medicaid requires coinsurance of 30 percent and the cash-out option offers transfers of around $6,000, the in-kind Medicaid subprogram is composed exclusively of people in the top 25 percent of the medical need distribution.