Appendix for:

The Effect of the Affordable Care Act on Diabetes Care at Major Health Centers: Newly Detected Diabetes and Diabetes Medication Management

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Table of Contents

Data source 3
Individual-level insurance status information 3
Expansion status 3
Statistical analysis 3
Adjustment variables 4
Definition of diabetes 4
Diabetes medications 4
References 14
Data source

This study used electronic health record (EHR) data from 2010-2018 from 11 health systems within the CAPriCORN and GPC PCORnet Clinical Data Research Networks. The GPC network was represented by the University of Kansas Medical Center, Medical College of Wisconsin, University of Nebraska Medical Center, Indiana University, University of Missouri School of Medicine, the University of Iowa Medical Center, and the University of Texas Southwestern Medical Center. The CAPRICORN network was represented by Rush University Medical Center, Northwestern Medicine, Loyola Medical Center, and Cook County Health System. We studied only patients seen two or more times during the sample period (2011-2018) since the definition of diabetes we used requires the diagnosis to be confirmed in two separate patient encounters.

Individual-level insurance status information

The EHR data source had no reliable historic information on patient insurance status. We used patient residence in a low-income Census tract as a proxy for persons who were more likely to gain insurance under the ACA. We used the Townsend Social Deprivation Index\(^2\) to identify Census tracts with overall lower social-economic status (SES), which we refer to as “low-income” tracts. Tracts with higher scores on the Townsend Index have lower median incomes and a larger proportion of non-elderly adults who gained health insurance as a result of the ACA. The Townsend index was calculated using five-year average data from the American Community Survey (ACS) for 2011-2015.\(^3\) It is an aggregate measure based on the percentage of households without a car, households with more than one person per room, percent renting rather than owning housing, and percent unemployed. The value of the index is not interpretable, only relative ranking is important. We computed Townsend index values for all census tracts nationwide and assigned tracts to quintiles where the fifth quintile is representative of the most economically deprived area and the first quintile represents affluent areas. While the ACS variables used in the Townsend index are not directly related to health, the Townsend index quintiles do identify deprived neighborhoods well,\(^4\) and these quintiles are associated with cancer risk,\(^5\) poor overall health,\(^6,7\) and depression.\(^8\) We used residence in quintiles four and five as a proxy for a greater likelihood of gaining insurance due to the ACA.

Expansion status

We assessed whether trends for treated persons were different in Medicaid expansion versus non-expansion states. Our 8 states include three that implemented the ACA Medicaid expansion on 1 January 2014 (Illinois, Iowa, and Wisconsin (partial expansion, to 100% of FPL)), one state that expanded on 1 February 2015 (Indiana), and four non-expansion states (Kansas, Nebraska, Missouri, and Texas). Because Indiana expanded Medicaid in 2015 instead of 2014, we performed sensitivity analyses in which instead of treating Indiana as an expansion state, we excluded it from the sample, with similar results.

Statistical analysis

We used a combined age discontinuity and DiD design – DiD regressions, applied to persons within an age band around age 65. We compared changes in outcomes for low-income persons under age 65 to low-income persons over age 65, before and after the ACA health insurance expansion. For each outcome variable, we estimated the following regression:
where $Y$ is the outcome of interest for each state; $\theta_{\text{State}}$ is the state fixed effects (FE); $\lambda_t$ are the year FE; $\beta_0$ is a constant term; $\beta_1$ is a treatment (young) group dummy variable = 1 if, under 65, 0 if over 65; Post is a dummy variable for the ACA expansion period (equal to 1 for 2014-2018; equal to 0 for 2011-2013; note that Post, if included in the regression, would be absorbed by the year FE); $\delta$ is the treatment effect, which captures the ACA effect on the outcome. If $\delta > 0$, this indicates an increase in the outcome for younger patients from low-income Census tracts, relative to older patients from these tracts, after ACA implementation in 2014. We use a similar model with separate annual dummy variables for the treatment and control groups to obtain the annual data for the Figures, see Appendix for details. The outcome variables are proportions, so the DiD estimate represents an after-minus-before change in the proportion.

Statistical analyses were conducted with Stata-MP 15 and figures were created using MATLAB version R2016b.

**Adjustment variables**

All regressions included state and year fixed effects to account for time-invariant state level and secular factors that might affect our results. We did not include other covariates because these should be similar for treated and control persons, given that we study below- versus above-65 year old persons from the same low-income Census tracts.

**Definition of diabetes**

We identified “detected” diabetes in adult patients using a modified version of the SUPREME-DM criterion. A patient was classified as having diabetes if the EHR contained (i) prescription of diabetes-specific medications at least once, or (ii) on two different visits one observed (a) a diabetes diagnosis code, or (b) HbA1c $\geq$ 6.5%, or (c) random glucose $\geq$ 200 mg/dL, or (d) fasting glucose $\geq$ 126 mg/dL, or (iii) prescription of a diabetes-relevant but not a diabetes-specific medication (for example, metformin) plus a single occurrence of one of the events in category (ii). Because we studied only patients age 55-74, we did not need to employ an exclusion for gestational diabetes. Newly detected diabetes was assigned to the earliest date among these events. We refer to diabetes detection rather than incidence because the true incidence is not known.

**Diabetes medications**

We defined diabetes-related medications to include both diabetes-specific medications (sulfonylurea, insulin, biguanide, thiazolidinedione, $\alpha$-glucosidase inhibitor, incretin mimetic, meglitinide, amylin analog, or dipeptidyl peptidase inhibitor) and non-specific medications that can also be prescribed for other conditions (metformin, any thiazolidinedione, or exenatide). We used information on both prescription and dispensing, using both medication name and medication code fields (Appendix, Table S1). We note, however, that dispensing information is often incomplete because many patients have prescriptions filled at a pharmacy outside the health system, and these fills are typically not captured in the system’s EHR. We treated any instance of diabetes-related medication prescription or dispensing during a year as indicating medication access for that year. To address censoring due to patients no longer receiving care within a health system, we followed patients with diabetes from the date of diabetes detection.
through the last recorded visit date in the EHR. We treat a visit anytime during a particular year as implying presence in the EHR for that year.
Table S1. Diabetes management medications. The NDC codes are normalized to PCORI CDM format prior the use in this work.

<table>
<thead>
<tr>
<th>Generic name (Brand Name)</th>
<th>SQL-specific regular expression</th>
<th>RXNORM_CUI</th>
<th>NDC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Alpha-glucosidase inhibitors:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACARBOSE (PRECOSE, GLUCOBAY)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%acarbose%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MIGLITOL (GLYSELT)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%miglitol%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VOGLIBOSE (BASEN)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%voglibose%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dipeptidyl Peptidase IV Inhibitors:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALOGLIPTIN (NESINA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%alagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANAGLIPTIN (SUHY)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%anagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LINAGLIPTIN (TRADIENTA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%linagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
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<tr>
<td>SAXAGLIPTIN (ONGLYZA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%saxagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
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<td></td>
</tr>
<tr>
<td>SITAGLIPTIN (JANUVIA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%sitagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
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<td></td>
</tr>
<tr>
<td>TENLAGLIPTIN (TENELIA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%tenlagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VILDAGLIPTIN (GALVUS, ZOMELIS)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%vildagliptin%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Glucagon-like Peptide-1 Agonists:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LIXISENATIDE (ADLYXIN, LYXUMIA)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%lixisenatide%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
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<tr>
<td>ALBIGLUTIDE (TANZEUM, EPERZAN)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%albiglutide%') or UPPER(RAW_RX_MED_NAME) like</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DULAGLUTIDE (TRULICTY)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%dulaglutide%') or UPPER(RAW_RX_MED_NAME) like</td>
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<td></td>
</tr>
<tr>
<td><strong>Sodium glucose cotransporter (SGLT) 2 inhibitors:</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>DULAGLUTIDE (TRULICTY)</td>
<td>UPPER(RAW_RX_MED_NAME) like UPPER('%dulaglutide%') or UPPER(RAW_RX_MED_NAME) like</td>
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</tbody>
</table>

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### Insulins:
- **Insulin Aspart (NovoLog)**
- **Insulin Glulisine (Apidra)**
- **Insulin Lispro (Humalog)**
- **Insulin Inhaled (Afrezza)**
- **Regular Insulin (Humulin R, Novolin R)**
- **Intermediate-Acting Insulins:**
  - Insulin NPH (Humulin N, Novolin N)
  - Insulin Detemir (Levemir)
- **Insulin Glargine (Lantus, Lantus SoloStar, Toujeo, Basaglar)**
- **Insulin Degludec (Tresiba)**
- **Insulin Aspart Protamine/Insulin**

### Amylinomimetics:
- **Pramlintide (Symlin, SymlinPen 120, SymlinPen 60)**

### Meglitinides:
- **Nateglinide (Starlix)**
- **Repaglinide (Prandin, Novonorm)**

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**ASPART (NOVOLOG 50/50, NOVOLOG 70/30)**
**INSULIN LISPRO PROTAMINE/INSULIN LISPRO (HUMALOG 50/50, HUMALOG 75/25)**
**ACTRAPID**
**HYPURIN**
**ILETIN**
**INSULATARD**
**INSUMAN**
**MIXTARD**
**NOVOMIX**
**NOVORAPID**
**ORALIN**
**ABASAGLAR**
**RYZODEG**
**V-GO**

**Combinations:**
- LINAGLITIN-EMPAFLIFLOZIN (GLYXAMBI)
- SITAGLIPTIN-SIMVASTATIN (JUVISYNC, EPISTATIN, SYNVINOLIN, ZOCOR)
- METFORMIN-ALOGLIPTIN (KAZANO)
- METFORMIN-CNAGLIFLOZIN (INVOKAMET)
- METFORMIN-DAPAGLIFLOZIN (XIGDUO XR)
- METFORMIN-EMPAFLIFLOZIN (SYNJARDY)
- METFORMIN-GLIPIZIDE (METAGLIP)
- METFORMIN-GLYBURIDE (GLUCOVANCE)
- METFORMIN-LINAGLIPTIN (JENTADUETO, JENTADUETO XR)
- METFORMIN-REPAGLINIDE (PRANDIMET)
- METFORMIN-SAXAGLITIN (KOMBIGLYZE XR)
- METFORMIN-SITAGLIPTIN (JANUMET, JANUMET XR)
- METFORMIN AND VILDAagliptin (EUCREAS)
### Glucagon-like Peptide-1 Agonists:

- **Exenatide (Byetta, Bydureon)**
- **Liraglutide (Victoza, Saxenda)**

### Thiazolidinediones:

- **Rosiglitazone (Avandia)**
- **Pioglitazone (Actos)**
<table>
<thead>
<tr>
<th>TROGLITAZONE (NOSCAL, RESULIN, REZULIN, ROMOZIN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>on UPPER(RAW_RX_MED_NAME) like UPPER('%DAPAGLIFLOZIN%') or on UPPER(RAW_RX_MED_NAME) like UPPER('%LIXISENATIDE%') or on UPPER(RAW_RX_MED_NAME) like UPPER('%ROMOZIN%') or on UPPER(RAW_RX_MED_NAME) like UPPER('%SAXAGLIPTIN%') or on UPPER(RAW_RX_MED_NAME) like UPPER('%TROGLITAZONE%')</td>
</tr>
</tbody>
</table>

and not (UPPER(RAW_RX_MED_NAME) like UPPER('%ACARBOSE%') or UPPER(RAW_RX_MED_NAME) like UPPER('%MEGLITIN%') or UPPER(RAW_RX_MED_NAME) like UPPER('%VFAGLIPINS%') or UPPER(RAW_RX_MED_NAME) like UPPER('%SAXAGLIPTIN%') or UPPER(RAW_RX_MED_NAME) like UPPER('%TROGLITAZONE%'))
### Combinations:

- **METFORMIN-PIOGLITAZONE** (ACTOPLUS, ACTOPLUS MET, ACTOPLUS MET XR, COMPETACT)
- **METFORMIN-ROSIGLITAZONE** (AVANDAMET)
- **INSULIN-LIRAGLUTIDE**
- **ERTUGLIFLOZIN-METFORMIN**

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**UPPER%GLYBURMIDE SODIUM %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%GLIMPEN TIDE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%NATGLOLIDE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%REFAGLIND \) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%GLULISINE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%REGULAR INSUL IN %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%NOVAPH %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%DETEMIR %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%GLARGINE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%DETEMIR %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%LISPRO %\) or**
**UPPER%DEGLUDEC %\) or**
**UPPER%GLARGINE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%PRAMLINTIDE %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%HYPURIN %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%ACTRAPID6%\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%HYPURINS %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%VILEINS %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%INSULATARD %\) or**
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**UPPER%INSUMAM %\) or**
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**UPPER%MIXTARD %\) or**
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**UPPER%NOVOMED %\) or**
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**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%RYZODEG %\) or**
**UPPER%RAW_RX_MED_NAME\) like**
**UPPER%V-GO %\) or**
**UPPER%RAW_RX_MED_NAME\) like

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References


