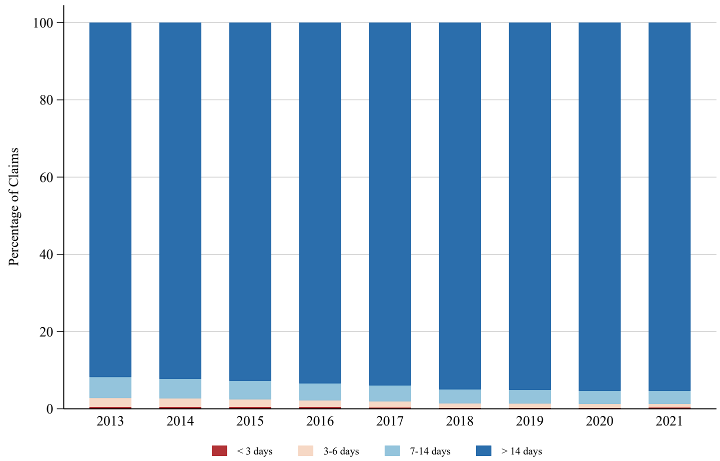
Appendix

A Appendix Figures

Figure A.1: Distribution of OxyContin Claims by Days of Supply

This figure shows the annual distribution of OxyContin prescription claims by days of supply. Panel (a) presents the distribution for initial-use claims, and Panel (b) presents the distribution for all claims, including refills. All claims are drawn from the Marketscan Outpatient Drug Claim database, and OxyContin is identified by National Drug Code (NDC) numbers beginning with 59011.

Panel A: Initial-Use OxyContin Claims by Days of Supply



Panel B: OxyContin Claims by Days of Supply

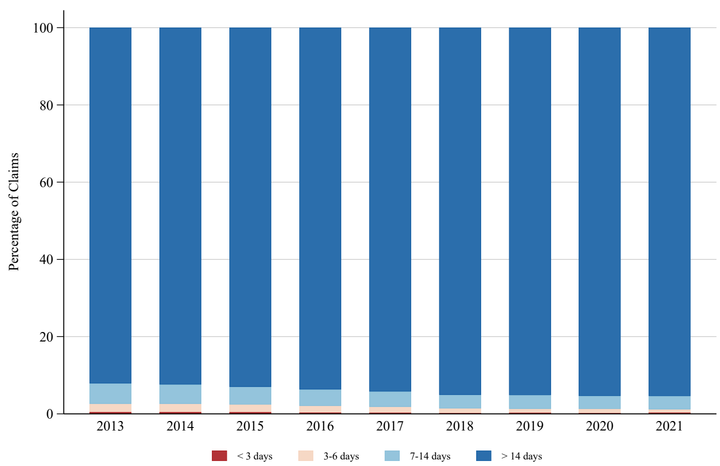


Figure A.2: Robustness of the Parallel Trend: Using 2015 as the Reference Year

This figure plots the treatment dynamics of LA opioid prescribing associated with Practice Fusion's manipulation. Panels (a)–(c) display the β_c coefficients from Equation (2) with 95% confidence intervals (solid lines). The x-axis indicates calendar years. The base year is 2015 (red dashed line), the year before manipulation. The green dashed line marks the suspension of the manipulation in 2019. Shaded regions indicate the 95% confidence interval of the average pre-treatment coefficients from 2013 to 2014.

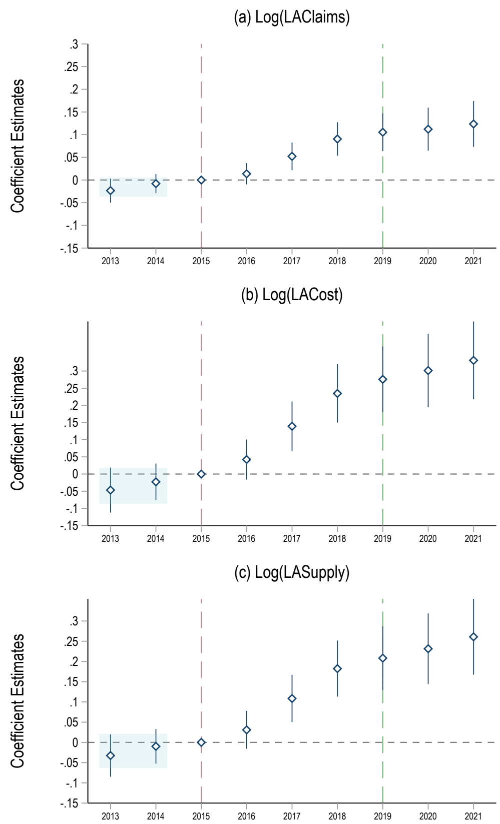


Figure A.3: Robustness of the Parallel Trend: 90% Confidence Interval with HonestDiD

Panels (a)–(c) present results from the HonestDiD procedure of Rambachan and Roth (2023), plotting 90% confidence intervals of the average treatment effects from 2017 to 2021 under alternative bounds on relative magnitudes M. Each M imposes that the post-treatment violation of parallel trends is no more than M times the maximum violation of parallel trends in the pre-treatment period (between consecutive periods).

(a) Log(LAClaims) Sensitivity Test (b) Log(LACost) Sensitivity Test (c) Log(LASupply) Sensitivity Test

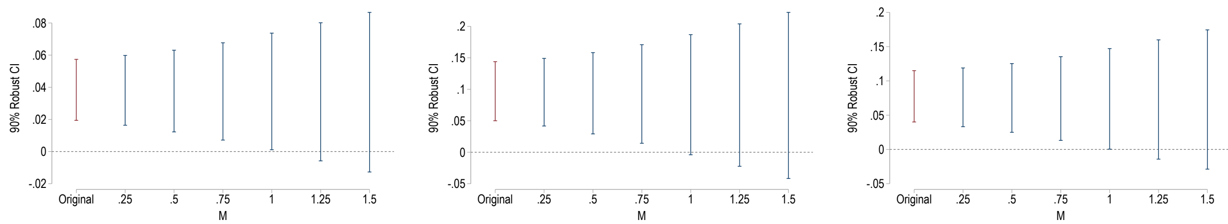
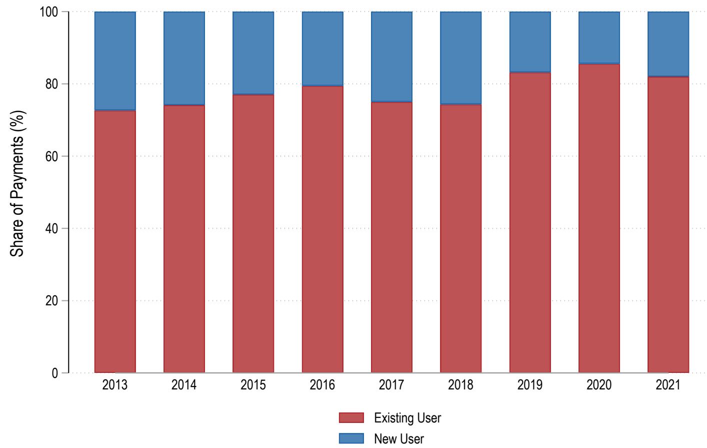


Figure A.4: Distribution of OxyContin Payments

This figure shows the annual distribution of OxyContin prescription payments by patient characteristics. Panel (a) presents the distribution by separating initial users from existing ones, and Panel (b) presents the distribution by separating patients with or without chronic pain conditions. All claims are drawn from the Marketscan Outpatient Drug Claim database, and OxyContin is identified by National Drug Code (NDC) numbers beginning with 59011.

Panel A: Share of OxyContin's Payments by New or Existing Users



Panel B: Share of OxyContin's Payments by Pain Conditions

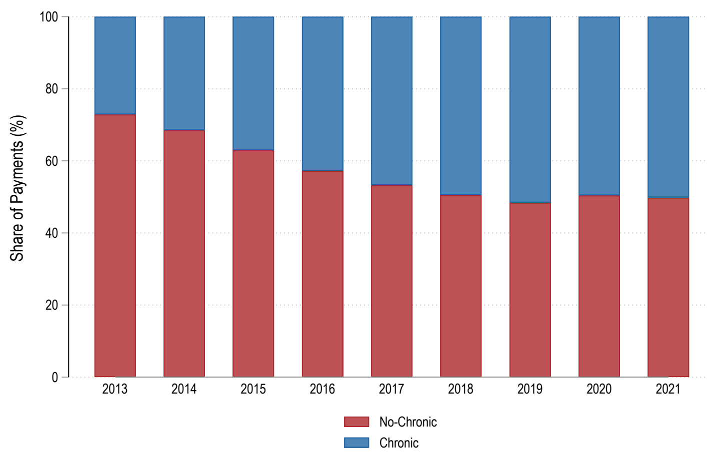


Figure A.5: Time Series of Google Search Interest of Practice Fusion

This figure shows the monthly search interest for "Practice Fusion" based on Google Trends data. The Google Trends index does not report absolute search volumes. Instead, it normalizes search intensity so that the highest observed month (January 2016–December 2022) equals 100. The dashed vertical line marks January 2020, when the U.S. Department of Justice announced its settlement with Practice Fusion.

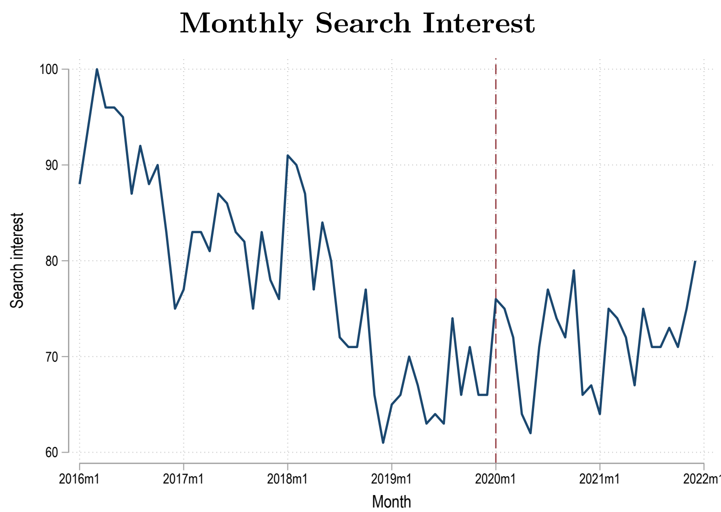
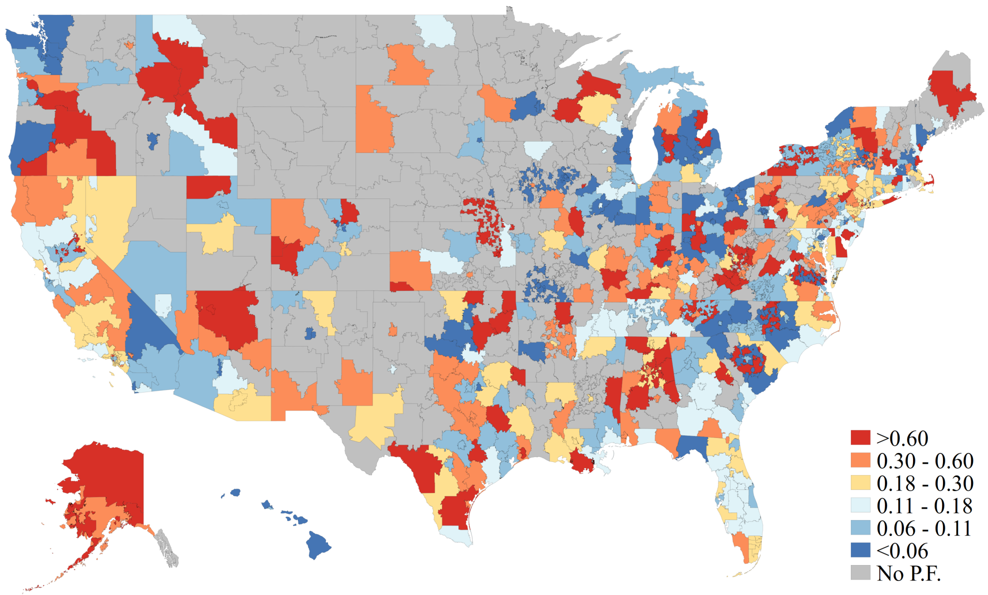


Figure A.6: Number of Recipients of Purdue Pharma Detailing

This figure plots the geographic distribution of Practice Fusion adopters and detailing recipients in our sample. Each area is a 3-digit zip code area. In each area, we calculate the fraction of Practice Fusion adopters and detailing recipients over the total number of physicians in that area from our sample. Areas without Practice Fusion adopters are marked in gray and dropped from the sample in our analysis.

Panel A: Distribution of Practice Fusion Adopters



Panel B: Distribution of Detailing Recipients

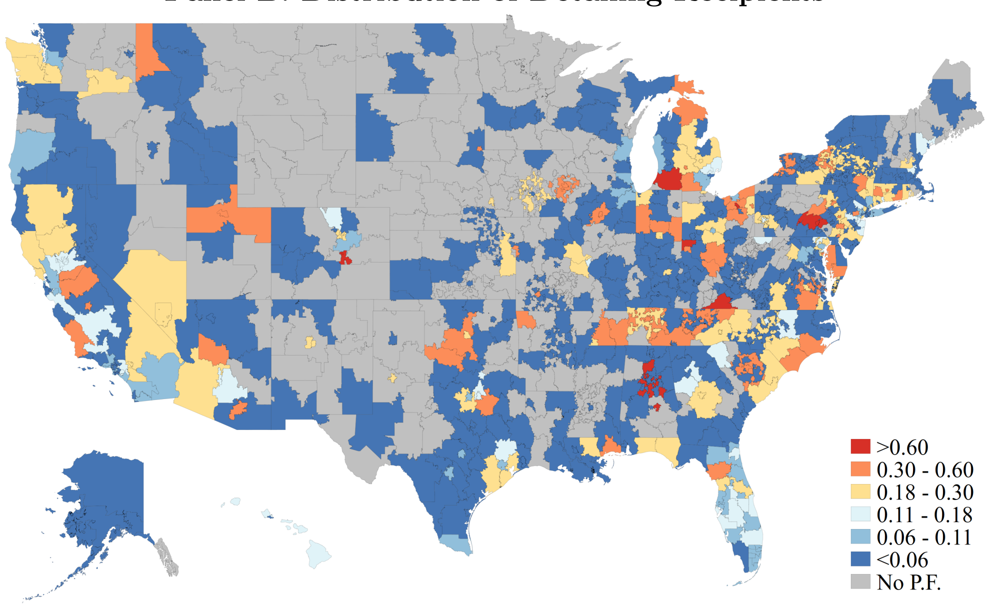
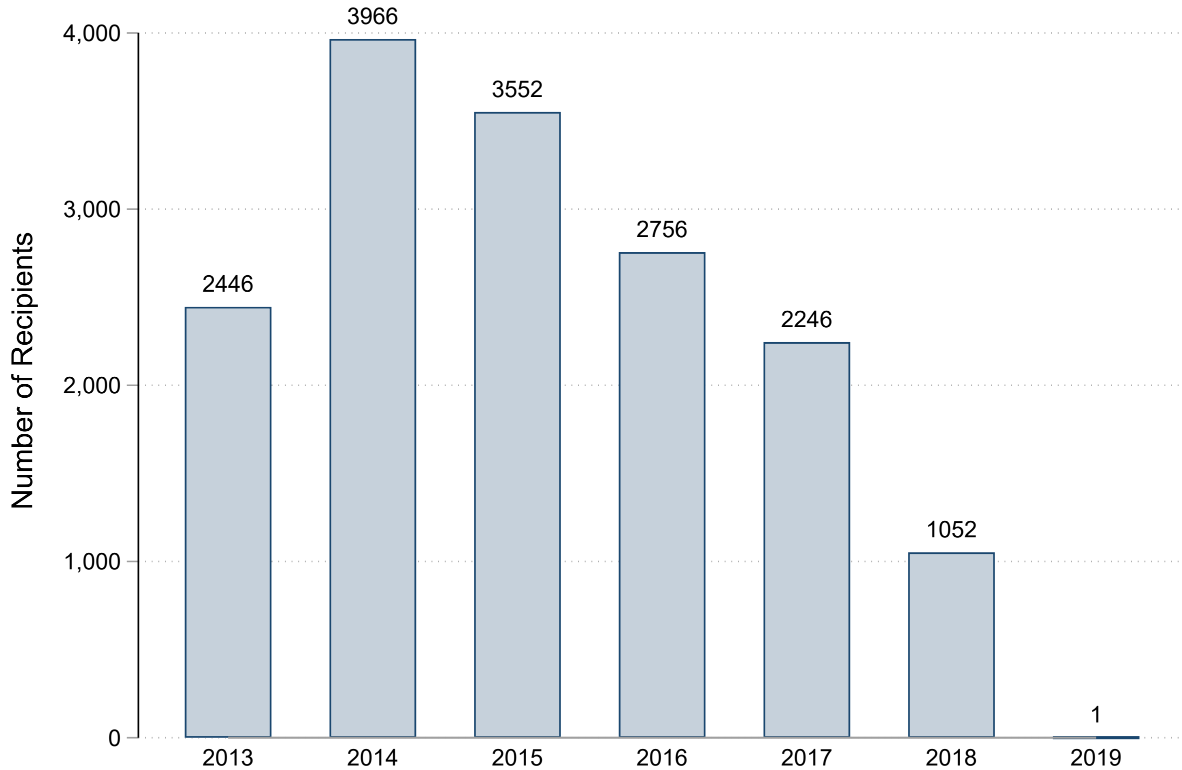


Figure A.7: Number of Recipients of Purdue Pharma Detailing

This figure plots the yearly number of recipients of Purdue Pharma detailing in our sample. We stopped at 2019 since in-kind payments to physicians were effectively suspended after Purdue Pharma filed for bankruptcy in 2019.



B Appendix Tables

Table B.1: Top 5 Specialty in the Sample

This table reports the top five physician specialties in the sample. Percent indicates the share of physicians within each specialty. Specialties are ranked by frequency, from most to least common. Cumulative Percent shows the cumulative share of physicians up to each specialty.

Specialty	**Percent**	**Cumulative Percent**
Family Medicine	31.95	31.95
Internal Medicine	28.18	60.13
Cardiovascular	4.64	64.77
Specialist	2.92	67.69
Gastroenterology	2.80	70.49

Table B.2: Adoption and Switching of Practice Fusion

This table reports the adoption and switching of Practice Fusion. Column (1) studies whether Practice Fusion adoption is associated with more LA claims in 2015. Columns (2) to (4) study whether the pre-treatment LA claims are associated with more Practice Fusion adoption, switching to Practice Fusion, or any kinds of changes in EHR in 2016. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *PF*	(2) *PF*	(3) *PF Swtich*	(4) *Any Swtich*
$Log(LAClaims)_t$	-0.049***			
	(-6.197)			
$Log(LAClaims)_{t-1}$		-0.050***	0.006	0.004
		(-6.279)	(0.183)	(0.376)
Sample	2015	2016	2016	2016
N	56,906	55,731	55,731	55,731

Table B.3: Short-term and Long-term Impacts on the Unique Number of Beneficiaries

This table provides the evidence that treated physicians significantly prescribe LA opioid drugs to significantly more patients. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $LABene_{i,t}$ is the unique number of Medicare beneficiaries receiving LA opioids from physician i in year t. $BeneIncrease_{i,t}$ is one if the unique number of Medicare beneficiaries receiving LA opioids from physician i in year t strictly increases compared to the previous year. $Avg\ Supply_{i,t}$ is the average days of supply per beneficiary in a year, estimated by dividing $LASupply_{i,t}$ with $LABene_{i,t}$. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects, area-specialty fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Short-term Impacts

	(1) *Log(LABene)*	(2) *BeneIncrease*	(3) *Avg Supply*	(4) *Log(Avg Supplu)*
$PF \times Post$	0.028***	0.005*	3.094	0.021
	(3.051)	(1.660)	(1.071)	(0.857)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	305,082	252,014	24,110	24,110
Adj. R^2	0.72	0.22	0.73	0.77

Panel B: Long-term Impacts

	(1) *Log(LABene)*	(2) *BeneIncrease*	(3) *Avg Supply*	(4) *Log(Avg Supplu)*
$PF \times Post$	0.043***	0.006**	-0.856	0.008
	(2.957)	(1.968)	(-0.158)	(0.186)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	292,094	238,963	17,859	17,859
Adj. R^2	0.61	0.19	0.72	0.75

Table B.4: The Long-term Impacts in the Mover Sample: 5-digit Zip Code

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the mover sample. The sample consists of annual observations among the physicians that move to a new 5-digit zip code after 2019. The sample period is from 2013 to 2015, and 2019 to 2021, i.e. the pre-treatment and post-treatment phases. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $LARate_{i,t}$ is the percentage of long-acting opioid claims out of all opioid claims by physician i in year t. Control variables include *AvgAge*, *MalePct*, *BlackPct*, *HispanicPct*, *DualPct*, and *AvgRisk*. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*
$PF \times Post$	0.198***	0.510***	0.428***	1.060**
	(2.689)	(3.106)	(3.215)	(2.513)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	24,852	24,852	24,852	24,852
Adj. R^2	0.68	0.64	0.65	0.57

Table B.5: The Long-term Impacts in the Mover Sample: State

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the mover sample. The sample consists of annual observations among the physicians that move to a new state after 2019. The sample period is from 2013 to 2015, and 2019 to 2021, i.e. the pre-treatment and post-treatment phases. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $LARate_{i,t}$ is the percentage of long-acting opioid claims out of all opioid claims by physician i in year t. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*
$PF \times Post$	0.395***	0.979***	0.835***	2.452**
	(3.403)	(3.613)	(3.841)	(2.401)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	5,156	5,156	5,156	5,156
Adj. R^2	0.59	0.56	0.56	0.51

Table B.6: The Long-term Impacts in the Mover Sample: Any Affiliation Changes

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the mover sample. The sample consists of annual observations among the physicians that have any affiliation changes after 2019. The sample period is from 2013 to 2015, and 2019 to 2021, i.e. the pre-treatment and post-treatment phases. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $LARate_{i,t}$ is the percentage of long-acting opioid claims out of all opioid claims by physician i in year t. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*LARate*
$PF \times Post$	0.103***	0.275***	0.197***	0.369**
	(3.451)	(4.042)	(3.527)	(2.228)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	187,524	187,524	187,524	187,524
Adj. R^2	0.72	0.69	0.69	0.61

Table B.7: States with Opioid Use Limits

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the sample of states with limits on days of supply for opioid prescription. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $Log(SAClaims)_{i,t}$ is the logarithm of one plus number of short-acting opioid claims. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Short-term Impacts				**Long-term Impacts**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*Log(SAClaims)*	*Log(LAClaims)*	*Log(LACost)*	*Log(LASupply)*
$PF \times Post$	0.057***	0.143***	0.110***	-0.014	0.092***	0.258***	0.189***
	(2.891)	(3.185)	(3.072)	(-0.596)	(2.676)	(3.394)	(3.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145,453	145,453	145,453	145,453	139,125	139,125	139,125
Adj. R^2	0.80	0.76	0.77	0.87	0.73	0.70	0.70

Table B.8: States with Comprehensive PDMP Adoption by 2018

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the sample of states with comprehensive PDMP adoption by 2018. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $Log(SAClaims)_{i,t}$ is the logarithm of one plus number of short-acting opioid claims. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Short-term Impacts				**Long-term Impacts**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*Log(SAClaims)*	*Log(LAClaims)*	*Log(LACost)*	*Log(LASupply)*
$PF \times Post$	0.088***	0.199***	0.158***	0.007	0.133***	0.338***	0.266***
	(3.353)	(3.369)	(3.303)	(0.208)	(2.883)	(3.457)	(3.257)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	89,956	89,956	89,956	89,956	86,096	86,096	86,096
Adj. R^2	0.79	0.76	0.76	0.87	0.73	0.69	0.70

Table B.9: States with Comprehensive PDMP Adoption by 2021

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription in the sample of states with comprehensive PDMP adoption by 2021. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $Log(SAClaims)_{i,t}$ is the logarithm of one plus number of short-acting opioid claims. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Short-term Impacts				**Long-term Impacts**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*Log(SAClaims)*	*Log(LAClaims)*	*Log(LACost)*	*Log(LASupply)*
$PF \times Post$	0.086***	0.212***	0.164***	-0.000	0.136***	0.350***	0.267***
	(4.899)	(5.353)	(5.069)	(-0.019)	(4.748)	(5.584)	(5.159)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	201,139	201,139	201,139	201,139	192,769	192,769	192,769
Adj. R^2	0.80	0.76	0.76	0.87	0.73	0.69	0.70

Table B.10: States with High Google Search Interest in 2020 and 2021

This table provides the results on the long-term impacts of Practice Fusion's CDS on opioid prescription by whether physicians are in states with high Google search interest after the settlement. This sample has the pre-treatment and post-treatment periods. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $HighAware$ is one if physician i's states have high (above median) search interest of "Practice Fusion" on Google in 2020 and 2021, and zero otherwise. $HighAware$ is not absorbed by Physician FEs because physicians may move to new states. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $Log(SAClaims)_{i,t}$ is the logarithm of one plus number of short-acting opioid claims. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*
$PF \times Post$	0.223***	0.505***	0.393***
	(4.392)	(4.840)	(4.519)
$PF \times Post$	-0.135**	-0.249**	-0.204**
$\times HighAware$	(-2.359)	(-2.068)	(-2.046)
$HighAware$	-0.034	-0.081	-0.060
	(-0.930)	(-0.943)	(-0.857)
Controls	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes
N	291,530	291,530	291,530
Adj. R^2	0.72	0.69	0.69

Table B.11: Explicit Detailing

This table provides the results on the impacts of Purdue Pharma's detailing on opioid prescription. $Pudue_{i,t-1}$ is one if physician i has received in-kind payments from Purdue Pharma at $t-1$, and zero otherwise. $Detail_i$ is one if physician i had received in-kind payments from Purdue Pharma by 2019, and zero otherwise. PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $LARate_{i,t}$ is the percentage of long-acting opioid claims out of all opioid claims by physician i in year t. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Short-term Impacts

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*
$PF \times Post$	0.055***	0.147***	0.109***	0.209**
	(3.703)	(4.322)	(3.974)	(2.393)
$Purdue_{t-1} \times Post$	-0.133***	-0.221***	-0.186***	-0.617***
	(-6.625)	(-4.744)	(-5.021)	(-5.254)
$Purdue_{t-1}$	0.190***	0.399***	0.323***	0.675***
	(9.716)	(8.665)	(8.634)	(6.728)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	251,879	251,879	251,879	251,879
Adj. R^2	0.81	0.78	0.78	0.72

Panel B: Long-term Impacts

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*
$Detail \times Post$	-0.425***	-0.805***	-0.661***	-2.191***
	(-5.606)	(-4.866)	(-5.026)	(-4.969)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	283,358	283,358	283,358	283,358
Adj. R^2	0.71	0.68	0.68	0.60

Table B.12: Robustness Check: 5-digit Zip Code Areas

This table shows the robustness of Tables 2 by requiring the control group to be in the same 5-digit zip code areas and with the same specialty of the treatment group. Panel A estimates the effects in the short-term sample (2013 – 2018) and Panel B in the long-term sample (2013 – 2015 & 2019 – 2021). PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. $Log(LAClaims)_{i,t}$ is the logarithm of one plus $LAClaims_{i,t}$. $Log(LACost)_{i,t}$ is the logarithm of one plus $LACost_{i,t}$. $Log(LASupply)_{i,t}$ is the logarithm of one plus $LASupply_{i,t}$. $LARate_{i,t}$ is the percentage of long-acting opioid claims out of all opioid claims by physician i in year t. $Log(SAClaims)_{i,t}$ is the logarithm of one plus number of short-acting opioid claims. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Short-term Effects

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*	(5) *Log(SAClaims)*
$PF \times Post$	0.070***	0.172***	0.133***	0.403***	−0.004
	(3.895)	(4.209)	(4.010)	(3.741)	(−0.191)
Controls	Y	Y	Y	Y	Y
Area×Year FEs	Y	Y	Y	Y	Y
Physician FEs	Y	Y	Y	Y	Y
N	86,934	86,934	86,934	86,934	86,934
R^2	0.79	0.75	0.76	0.71	0.87

Panel B: Long-term Effects

	(1) *Log(LAClaims)*	(2) *Log(LACost)*	(3) *Log(LASupply)*	(4) *LARate*
$PF \times Post$	0.145***	0.376***	0.291***	0.500***
	(5.305)	(6.121)	(5.783)	(3.249)
Controls	Y	Y	Y	Y
Area×Year FEs	Y	Y	Y	Y
Physician FEs	Y	Y	Y	Y
N	83,059	83,059	83,059	83,059
R^2	0.72	0.69	0.69	0.63

Table B.13: Alternative Clustering by Vendors

This table shows the placebo test of Tables 2 using alternative clustering methods. Both panels follow from Table 2, except that standard errors are clustered at the vendor level in Panel A, and double clustered at the vendor and the 3-digit zip code level in panel B. t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Clustered by Vendor ID

	Short-term Impacts			**Long-term Impacts**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*Log(LAClaims)*	*Log(LACost)*	*Log(LASupply)*
$PF \times Post$	0.116***	0.308***	0.231***	0.059***	0.154***	0.114***
	(5.526)	(6.958)	(6.453)	(5.574)	(6.408)	(6.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	292,094	292,094	292,094	305,082	305,082	305,082
Adj. R^2	0.73	0.69	0.69	0.79	0.76	0.76

Panel B: Clustered by Vendor ID and Zip Codes

	Short-term Impacts			**Long-term Impacts**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(LAClaims)	*Log(LACost)*	*Log(LASupply)*	*Log(LAClaims)*	*Log(LACost)*	*Log(LASupply)*
$PF \times Post$	0.116***	0.308***	0.231***	0.059***	0.154***	0.114***
	(5.521)	(6.921)	(6.347)	(5.288)	(6.285)	(5.887)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	292,094	292,094	292,094	305,082	305,082	305,082
Adj. R^2	0.72	0.69	0.69	0.79	0.76	0.76

Table B.14: Placebo Test: Antibiotics and Antipsychotic

This table shows the placebo test of Tables 2 using Antibiotics and Antipsychotic. Panel A estimates the effects in the short-term sample (2013 – 2018) and Panel B in the long-term sample (2013 – 2015 & 2019 – 2021). PF_i is one if physician i adopts Practice Fusion's EHR, and zero otherwise. $Post_t$ is one if year t is greater or equal to 2016, and zero otherwise. Columns (1) and (2) are for Antibiotics and columns (3) and (4) are Antipsychotic. $Claims_{i,t}$ is the number of claims by by physician i in year t for the corresponding drug. $DrugCost_{i,t}$ is the dollar amount of drug costs by physician i in year t for the corresponding drug. Control variables include $AvgAge$, $MalePct$, $BlackPct$, $HispanicPct$, $DualPct$, and $AvgRisk$. Physician fixed effects, area-specialty fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Short-term Impacts

	(1)	(2)	(3)	(4)
	Antibiotics		**Antipsychotic**	
	Log(Claims)	*Log(DrugCosts)*	*Log(Claims)*	*Log(DrugCosts)*
$PF \times Post$	-0.025*	-0.012	-0.018	-0.023
	(-1.780)	(-0.515)	(-1.466)	(-0.785)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	305,082	305,082	223,193	223,193
Adj. R^2	0.86	0.81	0.91	0.89

Panel B: Long-term Impacts

	(1)	(2)	(3)	(4)
	Antibiotics		**Antipsychotic**	
	Log(Claims)	*Log(DrugCosts)*	*Log(Claims)*	*Log(DrugCosts)*
$PF \times Post$	-0.032	-0.018	-0.034*	-0.016
	(-1.478)	(-0.484)	(-1.911)	(-0.395)
Controls	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Area×Year FE	Yes	Yes	Yes	Yes
N	292,094	292,094	211,315	211,315
Adj. R^2	0.82	0.77	0.88	0.86

Table B.15: OLS Estimation of Equation (3)

This table estimates Equation (3) using the OLS regression:

$$p_{i,t} = \tau_0 \mathbf{I}\{i \in \mathbf{T}, t \geq 2016\} + \tau_1 \mathbf{I}\{i \in \mathbf{T}, t \geq 2017\} + \tau_2 \mathbf{I}\{i \in \mathbf{T}, t \geq 2018\} + \delta_i + \mu_{k,t} + \varepsilon_{i,t}.$$

$p_{i,t}$ is the prescription probability of physician i in year t. $\mathbf{I}\{i \in \mathbf{T}, t \geq s\}$ indicates whether physician i is in the treatment group and the calendar is greater or equal to s. No control variables are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) $p_{i,t}$
τ_0	0.012***
	(2.653)
τ_1	0.011***
	(2.672)
τ_2	0.012***
	(3.094)
Controls	No
Physician FE	Yes
Area×Year FE	Yes
N	314,145
Adj. R^2	0.76

Table B.16: Correlation between Direct Manipulation and Long-term Belief Distortion

This table exhibits the correlation between effects of direct manipulation and long-term belief distortion. Columns (1) to (3) are estimated in sample years 2016 to 2018. The remaining columns are estimated in sample years 2017 and 2018 due to the lagged explanatory variables. No control variables and fixed effects are included. Physician fixed effects and area-year fixed effects are included. Standard errors are clustered at the 3-digit zip code level, and t-statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) $\hat{\tau}_1$	(2) $\hat{\tau}_2$	(3) $\hat{\tau}_2$	(4) $\hat{\tau}_0$	(5) $\hat{\tau}_1$	(6) $\hat{\tau}_2$	(7) $\hat{\tau}_2$
$\hat{\tau}_0$	0.201***	0.174***	0.106***				
	(35.468)	(38.163)	(19.864)				
$\hat{\tau}_1$			0.336***				
			(50.583)				
$\hat{\tau}_{0,t-1}$				0.788***	0.213***	0.169***	0.087***
				(122.570)	(35.793)	(44.368)	(18.551)
$\hat{\tau}_{1,t-1}$							0.405***
							(67.119)
Controls	155,766	155,766	155,766	155,176	155,176	155,176	155,176
Physician FE	0.10	0.07	0.17	0.70	0.12	0.08	0.23

Table B.17: Variable Importance

This table exhibits variable importance in estimating the causal forest. Importance is calculated as a weighted sum of how many times feature j was split on at each depth in the forest, defined as

$$imp(x_j) = \frac{\sum_{k=1}^{4} \left(\frac{\text{\# Tree splits on } x_j \text{ at depth } k}{\text{\# All tree splits at depth } k} \right) k^{-2}}{\sum_{k=1}^{4} k^{-2}}.$$

Seniority is the number of years since physician's graduation in medical school. *PhysicanGender* is one if physician is female and zero otherwise. Other variables are defined in Table 1.

(1) *Variable*	(2) *Importance*
AvgAge	0.481
DualPct	0.175
AvgRisk	0.150
MalePct	0.059
Seniority	0.055
BlackPct	0.046
HispanicPct	0.030
PhysicanGender	0.002

C Model

Baseline Model Our conceptual framework features a physician's decision making process by maximizing the chance of correct prescription in a setting of dynamic learning. For physicians i facing case j at year t, they take a binary decision $a_{ij} \in \{0,1\}$, where $a_{ij} = 1$ indicates prescribing LA opioids. The underlying state $\omega_j \in \{0,1\}$, unobserved to the physician, indicates the true fitness of opioid usage. Physicians have disutility from both unnecessary prescription (choosing $a = 1$ when $\omega = 0$) and under-treatment (choosing $a = 0$ when $\omega = 1$), with payoffs modeled as

$$u_i = -\mathbf{I}\{a = 1, w = 0\}c_1 - \mathbf{I}\{a = 0, w = 1\}c_2. \tag{C.1}$$

In each case j, physicians observe patient characteristics Z_j and possibly a Practice Fusion pain alert, indicated by $s \in \{0,1\}$. They then form a belief $p_{it}(\omega|Z_j, s)$ and generate the likelihood ratio as

$$l_{it}(Z_j, s) = \frac{p_{it}(\omega = 1|Z_j, s)}{p_{it}(\omega = 0|Z_j, s)} = \underbrace{\frac{p_{it}(\omega = 1|Z_j)}{p_{it}(\omega = 0|Z_j)}}_{q_{it}(Z_j)} \times \underbrace{\frac{p_i(s|Z_j, \omega = 1)}{p_i(s|Z_j, \omega = 0)}}_{\delta_i(Z_j, s)}.$$

The decomposition follows from the Bayes rule and has an intuitive interpretation. $q_{it}(Z_j)$ is the prior belief of physician i observing Z_j in case j at year t. $\delta_i(Z_j, s)$ represents the periodic belief update due to CDS alerts. For simplicity, we assume δ_i is a static function (independent of t). Physicians in the control group do not suffer from possible short-term distortions so by definition, $\delta_i(Z_j, 0) = 1$. To model the long-term belief distortion, denote k by the number of years that a physician j has observed CDS alerts by t. We assume that every additional period of exposure to CDS manipulation will bias the likelihood upward by a certain degree:

$$q_{it}(Z_j) = q_{i0}(Z_j) \prod_{m=1}^{k} \gamma_i^m.$$

$q_{i0}(Z_j)$ is the initial belief without learning. γ_i^m is the belief bias due to the m^{th} interaction with manipulated CDS. Note that γ_i^m is implicitly a function of patient characteristics in that interaction. Finally, the payoff function in Equation (C.1) implies that physicians follow a simple cut-off strategy by

$$a_{it}(Z_j, s) = \mathbf{1}\left\{ q_{i0}(Z_j) \times \left(\prod_{m=1}^{k} \gamma_i^m \right) \times \delta_i(Z_j, s) \geq \frac{c_1}{c_2} \right\}. \tag{C.2}$$

The main prediction of this conceptual framework is that the treatment group will prescribe more LA opioids relative to the control group from 2016 to 2021, if $\left(\prod_{m=1}^{k} \gamma_i^m\right) \times \delta_i(Z_j, s) > 1$. To illustrate, consider two otherwise similar physicians but one uses Practice Fusion (treated) and one does not (control) in the following three cases. First, in the year of 2016 (the initial treatment period), both physicians have not interacted with manipulated CDS, and thus the second component in Equation (C.2) is one. The treated physician may have a higher prescription volume only due to the instantaneous belief update $\delta_i(Z_j, s)$. Second, in the year of 2020 (a post-treatment period), the last component equals one since the alerts are removed. But the treated physicians still have higher chances of prescription due to $\prod_{m=1}^{3} \gamma_i^m$ (three years of previous interaction). Lastly, in the year of 2017 (the second treatment period), the treatment group suffers both manipulation $\delta_i(Z_j, s)$

and belief distortion γ_i^1 after one period of learning.

Estimation via Multi-Arm Causal Forest Our data are aggregated at the physician-year level without the granular information of each visit j's decision a_{ij} and patient characteristics Z_j. Therefore, we need to estimate the expected probability of prescription based on Equation (C.2):

$$Pr(a_{it} = 1|\bar{X}_i) = \int \mathbf{1}\left\{ q_{i0}(z) \times \left(\prod_{m=1}^{k} \gamma_i^m \right) \times \delta_i(z,s) \geq \frac{c_1}{c_2} \right\} f\left(z|\bar{X}_i\right) dz. \tag{C.3}$$

In the above equation, $f\left(z|\bar{X}_i\right)$ is the conditional distribution of patient characteristics. We assume this distribution is characterized by physician-level variables $\bar{X}_i$, including the average patient beneficiary age, risk score, male fraction, African American fraction, Hispanic fraction, dual qualification (Medicaid and Medicare) fraction, physician seniority (years since graduation) and physician gender. Denote $p^T(\bar{X}_i)$ and $p^C(\bar{X}_i)$ as the equilibrium prescription probability for the treatment group and control group respectively. Following Equation (C.3), we can decompose $p^T(\bar{X}_i)$ into

$$\begin{aligned}
& p^T(\bar{X}_i) \\
= \ & \int \mathbf{1}\left\{ q_{i0}(z) \geq \frac{c_1}{c_2} \right\} f\left(z|\bar{X}_i\right) dz \\
+ \ & sgn\left(\delta_i - 1\right) \int \mathbf{1}\left\{ \frac{c_1}{c_2} > q_{i0}(z) \geq \frac{c_1}{c_2\delta_i} \right\} f\left(z|\bar{X}_i\right) dz \\
+ \ & \sum_{l=1}^{k} sgn\left(\gamma_i^l - 1\right) \int \mathbf{1}\left\{ \frac{c_1}{c_2\delta_i \times \left(\prod_{m=1}^{l-1} \gamma_i^m\right)} > q_{i0}(z) \geq \frac{c_1}{c_2\delta_i \times \left(\prod_{m=1}^{l} \gamma_i^m\right)} \right\} f\left(z|\bar{X}_i\right) dz.
\end{aligned}$$

Each line in the above equation has an intuitive interpretation. The second line represents the expected probability for a similar physician in the control group, i.e. $p^C(\bar{X}_i)$. The third line represents the marginal treatment effect due to direct manipulation, denoted by $\tau_0(\bar{X}_i)$. In the last line, each summation term represents the additional long-term impact due to the lth interaction, denoted by $\tau_l(\bar{X}_i)$.