Opioid Prescription Rates and Asset Prices — Assessment of Causal Effects

Keywords: Urban Economics, Stock Return Predictability, Health Economics and Economic Development, Opioid Prescription Rate, Real Estate Prices, Headquarter Location

Steven Wei Ho, Department of Economics, Columbia University
Jiahao Jiang, PhD Student, University of Virginia

Columbia University in the City of New York

University of Virginia

Introduction

Overdosing on opioids, a class of substances that acts upon opioid receptors to produce morphine-like effects, has become a serious social problem in recent years. We explore the link between county-level opioid prescription rates and asset prices, specifically, stock returns of firms headquartered in that county, as well as real estate prices. In order to establish the causal effects of opioid prescription rates on firm stock returns, we first apply an instrumental variable (IV) regression approach and use the number of clandestine drug laboratories in a county to be the instrumental variable. The results provide robust evidence that county-level opioid prescription rates have a negative causal effect on the equity returns of firms headquartered in that county. Furthermore, we analyze the effect of Medical Board of California's 2014 regulatory revision aimed at reducing controlled substance overdose due to prescriptions and implement a difference-in-differences (DiD) estimation. The DiD estimation results show that this policy change has a positive dynamic effect on Californian firms' equity returns. We also find that the opioid prescription reduction assistance program provided by California Health Care Foundation (CHCF) to certain counties in California helps to raise the median prices of existing single-family homes in those counties by $28,678 on average.

Data Description

- The raw data of prescriptions is collected by IQVIA Xponent which contains a sample of nearly 50,000 retail pharmacies that dispense about 90% of all prescriptions in the U.S. The sample period time is from the years 2006 to 2017.
- According to the Drug Enforcement Administration (DEA), law enforcement agents make reports if they detect special types of chemicals. The instrument variable: number of clandestine drug labs, is obtained by summing up the number of reports made by agents each month at the county level. The sample period time is from January 2004 to December 2018.
- Our sample period of firms' monthly returns starts from January 2009 and ends in December 2018. There are total of 5107 unique companies from the Center for Research in Security Prices (CRSP) database over the sample period.

Portfolio Analysis

We construct long-short portfolios that long firms' stocks in the bottom decile of the opioid prescription level while we short firms in the top decile of opioid prescription level. Since we focus on subsequent returns, the ranking of opioid prescription levels should be constructed based on data from previous years. Furthermore, the trend of opioid prescription rates conveys more information than the rates for each year as we can smooth out idiosyncrasies. Therefore, we calculate 3-year backward-looking moving average of opioid rates for the purpose of smoothing time series and reducing noise. The 3-year moving average of opioid prescription rates of county i in year t is constructed as: $MO_{it} = \frac{1}{3}\sum_{s=t-2}^{s=t} O_{is}$, wherein O represents the opioid prescription rate of a particular county in a given year and *MO* is the moving average of opioid rates. Each firm is assigned to a ranked decile portfolio, from 1 to 10, which corresponds to its *MO* in its headquarter location as of last year. Rank 1 corresponds to the opioid prescription level in the lowest decile; whereas Rank 10 corresponds to the highest decile. Figure 1.a shows that, the cumulative return of the constructed long-short portfolio is around 96%, from January 2009 to December 2018. The *t*-statistic of the monthly return difference between the highest ranked portfolio and the lowest ranked portfolio is 2.03, which is statistically significant at 5% level. Figure 1.b depicts the cumulative returns on the low-rate portfolio (blue) and high-rate portfolio (red), separately.

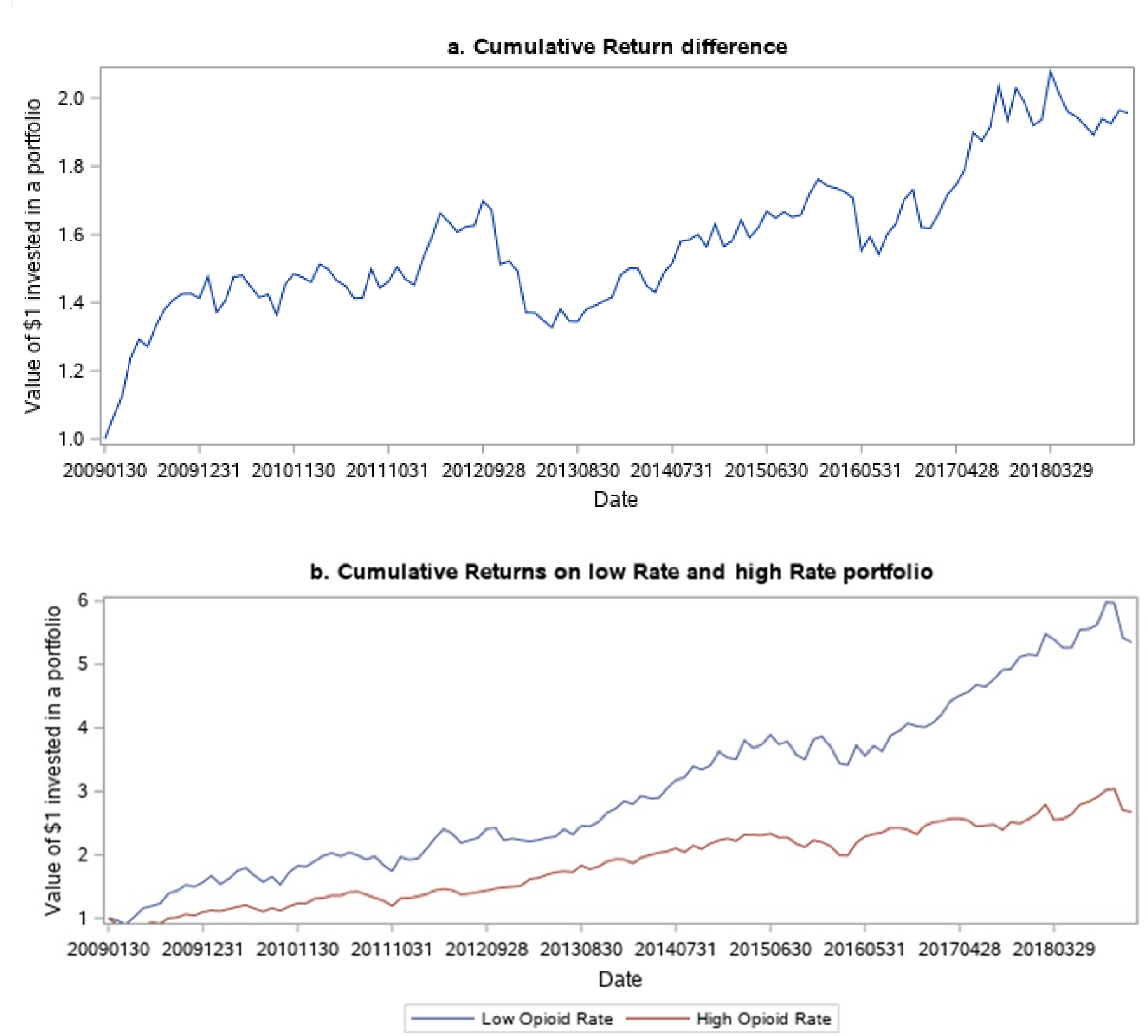

Figure 1: Cumulative Return Difference & Cumulative Returns on Low Rate and High Rate Portfolio from January 2009 to December 2018.

IV Regression & DID Estimation

To address any potential endogeneity concern and to rigorously analyze whether opioid rates have causal effects on future returns, we carry out IV (# of clandestine drug labs in a county) regressions on our sample. Specifically, we run the following two-stage least squares (2SLS) regression:

$$opioid_{it} = \delta + \phi d_{it} + \Gamma X_{it} + e_{it}$$

$$Return_{it} = \gamma + \beta opioid_{it} + \Gamma X_{it} + \epsilon_{it}$$

DV: RET	MA3			MA2		
	(1)	(2)	(3)	(4)	(5)	(6)
D.Opioid	-0.0031*	-0.0352*	-0.0335**	-0.0041*	-0.0281*	-0.0268**
	(-1.895)	(-1.742)	(-2.038)	(-1.890)	(-1.750)	(-2.051)
Lag Ret	-0.0120	-0.0258*	-0.0066	-0.0114	-0.0257*	-0.0064
	(-0.868)	(-1.816)	(-0.487)	(-0.822)	(-1.811)	(-0.476)
Comp Ret	0.0023	0.0017	0.0035	0.0023	0.0014	0.0031
	(1.049)	(0.742)	(1.544)	(1.009)	(0.594)	(1.381)
BM ratio	0.0068***	0.0069***	0.0061***	0.0071***	0.0065***	0.0057***
	(3.775)	(3.846)	(3.752)	(3.852)	(3.683)	(3.560)
Size	-0.0000	0.0005	0.0007	-0.0001	0.0006	0.0007
	(-0.032)	(0.652)	(0.982)	(-0.132)	(0.725)	(1.059)
Constant	0.0135	0.0398**	-0.0108	0.0126	0.0477**	-0.0058
	(1.254)	(2.298)	(-0.862)	(1.175)	(2.337)	(-0.405)
IV: MA of Drug Labs	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No	Yes	No
Year-month FE	No	No	Yes	No	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic (1st-stage)	4313.0985	124.2614	117.0124	1321.4553	353.5649	332.8672

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Instrumental variables regressions. The dependent variable (DV) is the firms' monthly returns (RET). The endogenous variable is the counties' opioid prescription levels. MA(*N*) means the opioid rates are taken to be the *N* year backward moving average. The instrumental variable is the backward looking moving average of number of clandestine drug labs for 6 years. Column (1) through (6) present the results with state fixed effect after removing the observations in which the total number of drug labs is less than or equal to 4. We add year fixed effect to Column (2) and (5), and add year-month fixed effect to Column (3) and (6). Both endogenous variable and instrumental variable are first-differenced in order to avoid the unit root problem.

In December 2014, the Medical Board of California called for a revision of "Guidelines for Prescribing Controlled Substances for Pain" to add additional directions and restrictions for physicians in their prescription of opioids. We utilize the difference-in-differences method (DiD) to estimate how these opioid restriction guidelines can affect firms' returns. The treatment group is firms in California and the control group is firms in Illinois. Firms located in Illinois can be considered as the control group since there is no guideline or regulation to restrict the prescription of opioids before 2018. Moreover, GDP growth rate and GDP per capita in Illinois are close to those in California. These conditions make Illinois be a valid treatment group. We run the following regression, that yields highly statistically significant results:

$$Return_{igt} = \delta + \sum^{T} \delta_\tau M_{\tau t} + \alpha_g + \beta DiD_{gt} + \Gamma_{gt} X_{igt} + \epsilon_{it}$$

	(1) N=1	(2) N=7
did	0.03424***	0.03848***
	(5.576)	(2.987)
Lag Ret	-0.02949***	-0.03708***
	(-4.222)	(-5.304)
Comp Ret	0.009055***	0.005954***
	(5.347)	(3.472)
BM ratio	0.007054***	0.006458***
	(6.151)	(5.633)
Size	-0.0002474	-0.0002298
	(-0.546)	(-0.509)
gtrend	-0.0004640***	0.01732***
	(-7.311)	(4.036)
gtrend2		-0.002022***
		(-4.463)
gtrend3		0.00008624***
		(3.929)
gtrend4		-0.000001770***
		(-3.200)
gtrend5		1.875e-08**
		(2.511)
gtrend6		-9.852e-11*
		(-1.931)
gtrend7		2.020e-13
		(1.462)
Constant	0.04295***	0.02447*
	(6.908)	(1.953)
R^2	0.036	0.043
Adjusted R^2	0.033	0.041

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: difference-in-differences (DiD) estimation. In order to relax parallel paths assumption, we use $\sum_{s=i}^{N} \beta_s t^s$ (*gtrend*) to capture differences in group dynamics before and after the treatment. Column (1) shows the results when the group dynamic effect is a linear time trend. Column (2) shows the results when the group dynamic effect is a polynomial time trend of degree 7 which further relaxes the parallel paths assumption.

DID for Assistance Program

Aside from stock returns, we study the causal effect of opioid prescriptions on real estate prices. The hypothesis is that a decrease in opioid prescription rates can cause an increase in real estate prices since the houses in low opioid drug infested areas are more attractive to buyers. In November 2015, the California Health Care Foundation (CHCF) started to provide technical assistance, aimed at opioid prescription reduction, to the coalitions of 23 counties. Therefore we choose these CHCF-supported counties to be the treatment group and those counties in California which did not receive CHCF assistance to be the control group. The dependent variable we use here is the monthly median prices of existing single-family homes obtained from the California Association of Realtors. The sample period is from January 2010 to December 2018, yielding highly statistically significant results on the real estate prices:

DV: Price	(1)	(2)	(3)
did	23207.4***	52394.0***	28678.1***
	(3.650)	(11.383)	(5.409)
unit		2.0797***	1.8632***
		(11.678)	(10.788)
density		459.52***	447.56***
		(32.767)	(32.992)
regulation		107034.3***	84854.9***
		(33.439)	(21.016)
Year-month FE	Yes	No	Yes
County FE	Yes	Yes	Yes
R^2	0.415	0.592	0.626
Adjusted R^2	0.404	0.588	0.618

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 shows the results of DiD estimation for CHCF assistance program in California. The dependent variable is the median price of existing single-family homes. Control variables include number of housing units (unit), population density (density) and the dummy variable indicating the restriction guidelines in place by the Medical Board of California (regulation). Column (1) presents the results without control variables while Column (2) and (3) contain control variables. The only difference between Column (2) and (3) is that Column (3) has both county fixed effect and year-month fixed effect but Column (2) only has county fixed effect.

Conclusion

Using county-level data, we investigate whether county-level opioid prescription rates are linked with the subsequent equity returns of firms headquartered in that county, as well as the real estate price of the county. First, we construct a long-short portfolio that longs firms' stocks with bottom-decile-level opioid prescription rates and shorts firms' stocks with top-decile-level opioid prescription rates (based on the previous year's backward-looking moving average of opioid prescription rates within that county). We find that the difference in returns between the long portfolio and short portfolio is statistically significant. Second, we run the panel regression and Fama-Macbeth regression (results presented in our full paper) of stock returns on opioid rates with additional financial control variables. The results suggest that there is a negative relationship between firms' returns and opioid prescription rates. Additionally, in order to determine if there is a causal relationship, we apply IV and DiD regressions. Overall, the results provide substantial evidence that opioid prescription rates in a firm's headquarter county have negative causal effect on firms' subsequent returns. We also find that the opioid prescription reduction assistance provided by California Health Care Foundation (CHCF) to certain counties in California raises the median prices of existing single-family homes in those counties by $28768.1 on average.